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DIPLOMA THESIS

Implementing the Principles of Circular Economy in the AEC Sector:

About the identification of reusable components using 360° Scans and Machine Learning

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DECLARATION OF AUTHORSHIP

I hereby certify that I have written the present thesis entitled “Implementing the Principles of Circular Economy in the AEC Sector: About the Identification of reusable components using 360° Scans and Machine Learning” independently and that the work contained herein is my own. All formulations and concepts taken verbatim or in substance from printed or unprinted material or the Internet have been cited according to the rules of good scientific practice and indicated by exact references to the original source. The same applies to all illustrations.

The present thesis has not been submitted to another university for the award of an academic degree in this form. I understand that the provision of incorrect information may have legal consequences.

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I ABSTRACT

The construction industry is a major contributor to waste generation and greenhouse gas emissions. Shifting the predominant linear mode of action to a circular model is crucial to reduce environmental impacts. Reuse has been identified as the most effective strategy in this regard. The lack of sufficient information about material composition and as-built data poses a significant challenge to reusing and recycling building resources. The development of appropriate tools and digital logistics systems can support the full implementation of the circular model in the built environment.

The sector's level of digitalization is still unsatisfactory and heavily reliant on analog work. Embracing accessible sensing and scanning tools and digital technologies can enhance the industry's digitalization efforts and promote more efficient and sustainable resource management. On-site digitization using cutting-edge technologies such as mobile photography, smartphone-based Light Detection and Ranging (LiDAR) devices, and 360° cameras with omnidirectional vision can help address this challenge. These technologies enable improved data collection and provide opportunities for more accurate and comprehensive information about building materials.

In this thesis, an object detection model is trained to identify reusable components in 360° images of a building indoors. The model "You Only Look Once", version 8s (YOLOv8s), is used to identify windows, doors, lights, heating, and sanitary in the newly generated 360° imagery dataset TUDataset. The data was captured in five selected buildings on the Technical University of Dresden Campus, Dresden, Germany, and comprises 136 object classes and approximately 2.400 images. The model serves as a proof-of-concept of the aptitude of 360° images for assessing the reuse potential of buildings. It achieved a satisfactory 63.4% mean Average Precision at Intersection over Union (IoU) of 0.5 (mAP50) and 37.1% mAP50 at IoU 0.5 to 0.95 (mAP50-95) on the TUDataset.

This thesis also explores state-of-the-art research and projects implementing CE strategies in practice. It identifies potentially reusable building components in a field search in component exchange platforms. In conclusion, the thesis proposes a solution that can capture the urban mining potential of existing buildings without incurring additional costs and serve as a planning foundation, thereby contributing to the transition towards a circular economy. The model detects all relevant building components and reduces time- and cost in the inventory process.

Keywords

Circular Economy, built environment, artificial intelligence, machine learning, object detection, 360° images, panorama images, component reuse

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V LIST OF ABBREVIATIONS

AEC	Architecture, Engineering and Construction
AI	Artificial Intelligence
AM/RM	Additive/ Robotic Manufacturing
BBSR	Federal Institure for Research on Building, Urban Affairs an Spatial Development
BCT	Block-Chain-Technology
BDA	Big Data and Analytics
BE	Built Environment
BREEAM	Building Research Establishment Environmental Assessment Method
C2C	Cradle to Cradle
CAD	Computer Aided Design
C&D	Construction and Demolition
CDB	Circular Digital Built Environment
CDW	Construction Demolition Waste
CDWM	Construction and Demolition Waste Management
CE	Circular Economy
CI	Construction Industry
CNN	Convolutional Neuronal Network
D-DAS	Disassembly and Deconstruction Analytics Systems
DfA	Design for Adaptability
DfD	Design for Disassembly, Design for Deconstruction
DFL	Dual Focal Loss
DT	Digital Technology
DT	Digital Twin
e-BKPH	Element-based Building Costing Plan for Building Construction
EEC	Embodied Energy and Carbon
EMF	Ellen MacArthur Foundation
EoL	End-Of-Life
EPR	Extended Producer Responsibility
ERP	Equirectangular Projection
EU	European Union
FoV	Field-of-View
GAN	Generative Adversarial Networks
GD	Gradient Descent
GDP	Gross Domestic Product
GHG	Gereenhouse Gas
GIS	Geographical Information Systems
ICT	Information and Communication Technologies
ILSVRC	ImageNet Large Scale Visual Recognition Challenge

IoT	Internet of Things
IoU	Intersection over Union
LCA	Life Cycle Assessment
LCC	Life Cycle Cost Analysis
LEED	Leadership in Energy and Environmental Design
LR	Learning Rate
LS	Laser Scanning
mAP	Mean Average Precision
ML	Machine Learning
MLP	Multilayer Perceptron
MP	Material Passports
MS	Modelling Simulation
NLP	Natural Language Processing
NMS	Non-Maximum-Suppression
NN	Neural Networks
PSP	(Multiple) Perspective Projection
RA	Recycled Aggregates
ReLU	Rectified Linear Unit
RFID	Radio Frequency Identification
RMM	Reusable Material Marketplaces
RQ	Research Question
SBB	Swiss Federal Railway
SGD	Stochastic Gradient Descent
SLR	Systematic Literature Review
SSD	Single Shot Dectector
SVM	Support Vector Machines
TLU	Threshold Logic Unit
UAS	Unmanned Aerial System
UM	Urban Mining
UMI	Urban Mining Index
WoS	Web of Science
YOLO	You Only Look Once

1 INTRODUCTION

1.1. MOTIVATION

The sustainable use of natural resources and the mitigation of climate change effects are currently the most significant challenges across science, business, society, and politics. (Braun et al., 2021) The construction industry, being the most resource-intensive sector in industrialized countries, contributes significantly to waste generation and greenhouse gas emissions (Ajayabi et al., 2019; Eberhardt et al., 2022; Gordon et al., 2023). It uses 50% of all materials consumed in Europe, accounting for 37% of the total waste in the European Union in 2020 (EUROSTAT, 2022). Additionally, it is responsible for 39% of the global energy-related greenhouse gas emissions. These impacts result from the industry's linear model of extraction, use, and disposal (Çetin et al., 2021, p. 1). To address these issues and reduce environmental impacts, a shift towards a circular model of the built environment is urgently needed (Çetin et al., 2021, p. 1).

This transition is especially crucial considering that the construction industry accounts for approximately 5.6% of the Gross Domestic Product (GDP) of the European Union (EU) in 2021. (United Nations Economic Commission for Europe, 2023). The built environment not only provides society with essential services, such as "*housing, food, healthcare, education, mobility, energy, water, communication, culture, and recreation [...]*" (Rios et al., 2022, p. 18). But it also represents *"the largest material stock"* (Hopkinson et al., 2019, p. 7) with an estimated 90% of all materials ever extracted residing in buildings and infrastructure (Kibert, 2022, p. 45). However, the end-of-life is the most impactful phase in terms of waste generation (Osobajo et al., 2022, p. 41), accounting for *"[...] up to 50 percent of national waste streams"* (Kibert, 2022, p. 260). The feasibility conditions of the circular model are linked to the economic efficiency of the processes (Ajayabi et al., 2019; Mangialardo and Micelli, 2018, p. 336). Direct recovery and cost-effective reuse of building products yield both cost savings and multiple resource and environmental benefits (Hopkinson et al., 2019, p. 3). However, one of the biggest challenges to reusing and recycling resources in buildings is the lack of sufficient information about material and substance composition and as-built data at the end-of-use phase (Çetin et al., 2021, p. 20; Honic et al., 2019; Raghu et al., 2022; Uotila et al., 2021; Xiong et al., 2022). Cutting-edge technologies are required for on-site digitization (Rahla et al., 2021), which is contrasted by the lack of appropriate tools and digital logistics systems (Charef et al., 2021; Osei-Tutu et al., 2022; Tirado et al., 2022) and the sector's unsatisfactory digitalization level (Charef, 2022, p. 1), which largely relies on analog work. In contrast, "accessible sensing and scanning tools, such as mobile photography and smartphone-based consumer grade Lidar devices" (Gordon et al., 2023,

p. 1), as well as 360° cameras with omnidirectional vision are being increasingly used for on-site digitization. Additionally, digital technologies and the wider field of Industry 4.0 have been suggested as having the potential to play a leading role in enabling and scaling the CE (Lacy and Rutqvist, 2015 as cited in; Okorie et al., 2018, p. 6)) and Artificial intelligence (AI) is having a key role within it (Darko et al., 2020, p. 1).

In this work, the potential of artificial intelligence (AI) and 360° images are synergistically combined to advance the implementation of the circular economy in the built environment. It couples 360° images and object detection to identify the reuse potential of building components within buildings. The work is based on the belief that by creating "quick, cost-effective, and straightforward methods for collecting data on the reusable building components at an urban scale" (Raghu et al., 2022, p. 579), reuse will prevail over conventional building practices.

1.2. SCOPE OF THE THESIS

This thesis aims to contribute to advancing circular economy practices in the built environment by developing a prototype digital solution that enables efficient detection and description of reusable components in the existing building stock. The investigation seeks to determine the extent to which machine learning algorithms can evaluate building component properties and facilitate the transition toward a more sustainable and circular construction industry. Therefore, the scope of this work encompasses several essential components. Firstly, it involves a literature review of successfully implemented circular economy projects in construction, both in research and practice. This review aims at identifying promising methods and areas that require further research, placing this thesis within the existing research field.

Additionally, this work focuses on a technical solution for identifying reusable components in an existing building. An approach is being pursued in which reusable components are recognized in images with machine learning. For this, an understanding of the reuse of components must first be created. Therefore, this thesis compiles and categorizes the component properties necessary to evaluate the reusability of selected components and building materials, classifying them into geometric and alphanumerical categories.

Furthermore, the analysis and evaluation of machine learning techniques for component identification, specifically assessing recyclability, are performed. An algorithm for component identification is implemented and trained on suitable datasets. The performance and effectiveness of these machine learning algorithms are evaluated in a demonstration scenario, utilizing 360° scans or raw data of component images from a chosen TU Dresden building, such as the Beyer-Bau or the Nürnberger Ei in Dresden, Germany. It is important to note that this work focuses on identifying building components and providing information for decision-making rather than making final determinations about their reusability. Hence, a predefined set of components with assumed general reuse potential is utilized.

The scope of this study is limited to the identification of reusable potential within the building construction sector of the AEC (Architecture, Engineering, and Construction) industry. Furthermore, the study does not encompass the full range of strategies within the Circular Economy principles that are applicable throughout the entire life cycle of a building project. It specifically focuses on the strategy of reuse and, to a lesser extent, recycling, within the end-of-life or next-use phase of the building.

1.3. RELEVANCE OF THEME

In a preliminary study (see Annex I), 35 relevant papers were found at the intersection of machine learning and circular economy. At the intersection of machine learning and 360° images, 118 papers were identified. This aligns with the findings of Guerrero-Viu et al. (2020), who state that research exists on the use of panoramic images for outdoor object recognition due to the increasing research on autonomous driving. However, there is a lack of comprehensive research on object recognition in indoor panoramic images (Guerrero-Viu et al., 2020, p. 568). No results were found at the intersection of CE and 360° images. The present study aims at adding value to construction practice by combining existing interdisciplinary approaches. To the authors' best knowing, this study is the first to utilize object detection in 360° images with the aim of identifying reuse potential of non-structural components in buildings.

1.4. ORGANIZATION OF THESIS

This first chapter introduces the motivation, relevance, and definition of concepts. The remainder of the thesis is structured as follows:

Section 2 explains the underlying concepts, including the theory of circular economy as well as the technical foundations for the practical part of this work, namely artificial intelligence, machine learning, object vision, and 360 scan methods.

Section 3 discusses the state of research and technology. Existing research trends are identified and explained through a literature review, and their implementation in practice is examined. Additionally, existing approaches to the use of machine learning in the context of circular economy are considered to determine if they can be further developed within the scope of this work.

Section 4 establishes the practical approach, with the first part identifying reusable components and their reuse parameters through a field study (4.1), and the second part critically evaluating suitable machine learning algorithms for component identification (4.2). The chapter concludes with the selection of a suitable machine learning model.

Section 5 presents the practical implementation of the algorithm, following the established machine learning pipeline. It starts with creating an annotated dataset to establish the data foundation (5.1 Data), followed by model training, validation, and final testing. The practical part concludes with an evaluation of the test results, critical assessment, and proposed improvements.

Finally, Section 6 elaborates on the discussion of results, the research contributions, implications for practice, and limitations. Lastly, an outlook is provided on research questions derived from this work and the concepts included.

2 DEFINITION OF CONCEPTS

This chapter provides a comprehensive definition of the key concepts that are central to this study. Specifically, this chapter covers Circular Economy principles within the Architecture, Engineering and Construction (AEC) sector (2.1), Artificial Intelligence (2.2), Machine Learning (2.3), Neural Networks (2.4), Computer Vision (2.5), and 360° Scans/Imaging (2.6). The purpose is to establish an understanding that supports the discussion and analysis in subsequent chapters.

2.1. CIRCULAR ECONOMY (CE)

The underlying concepts or “schools of thought” of the circular economy model date back to the 1970s, including the Club of Rome’s "Limits to Growth" theory, Braungart and McDonough’s ‘cradle to cradle’ concept, Stahel’s ‘performance economy’, and Lyle’s ‘regenerative design’ model, among others (ARUP, 2016, p. 16).

Yet, there is not one agreed unequivocal definition of the “Circular Economy” (Anastasiades et al., 2020; Kirchherr et al., 2016) In their analysis, Kirchherr et al. (2017) gathered and analyzed not less than 114 circular economy definitions, of which the majority depicted a combination of reduce, reuse and recycling activities. Key differences derive from the employment of the CE concept by different stakeholders (Okorie et al., 2018) and industry branches. For the purpose of this thesis, the definition developed by (Prieto-Sandoval et al., 2018, p. 613) will be adopted. It defines the circular economy as

> *“an economic system that represents a change of paradigm in the way that human society is interrelated with nature and aims to prevent the depletion of resources, **close energy and materials loops**, and facilitate sustainable development through its implementation at the micro (enterprises and consumers), meso (economic agents integrated in symbiosis) and macro (city, regions and governments) levels.” (Prieto-Sandoval et al., 2018, p. 613)*

In contrast with the prevalent linear economic model (Figure 1), which can be described as a unidirectional model or as an incomplete circle, that starts at the point of extraction and ends in disposal (Okorie et al., 2018), the circular economy is often described with resource loops. Drawing on the earlier works of the different schools of thought, the Ellen MacArthur Foundation developed the system or ‘butterfly’ diagram (Figure 2) founded on the notion that in a circular economy, materials continuously flow in two cycles: the technical and the biological cycle. (ARUP, 2016, p. 16) The natural cycle provides the groundwork for the technical cycle, and everything we use from the Earth comes from natural cycles. In a closed system like the Earth, technical materials can only be considered "lost" if they are irreversibly altered or made unusable without significant efforts, such as through chemical changes, pollution, or conversion to a gaseous state and release into the atmosphere." (Rosen, 2020, p. 21)

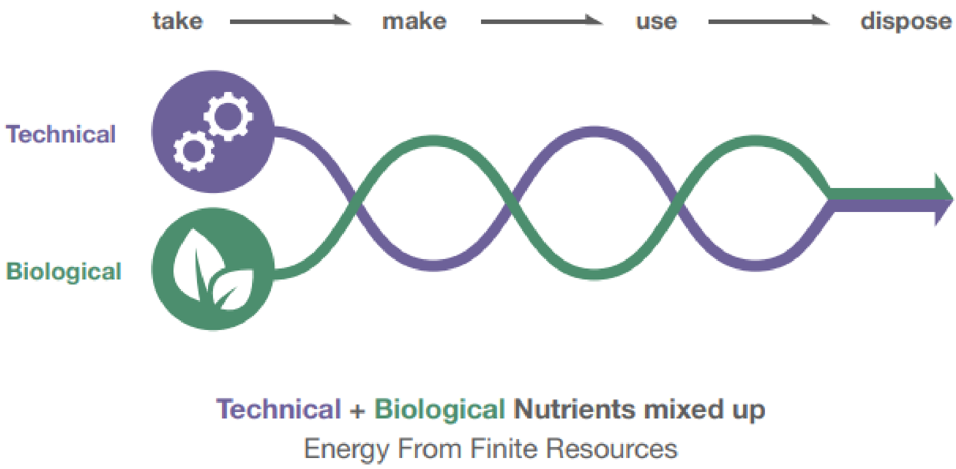

Figure 1: Linear Economy. In a linear economy or take-make-use-dispose model, materials are sourced, used, and finally disposed of as waste producing negative externalities that include rising carbon emissions, increased pressures on landfill, and unsustainable levels (ARUP, 2016, p. 10)

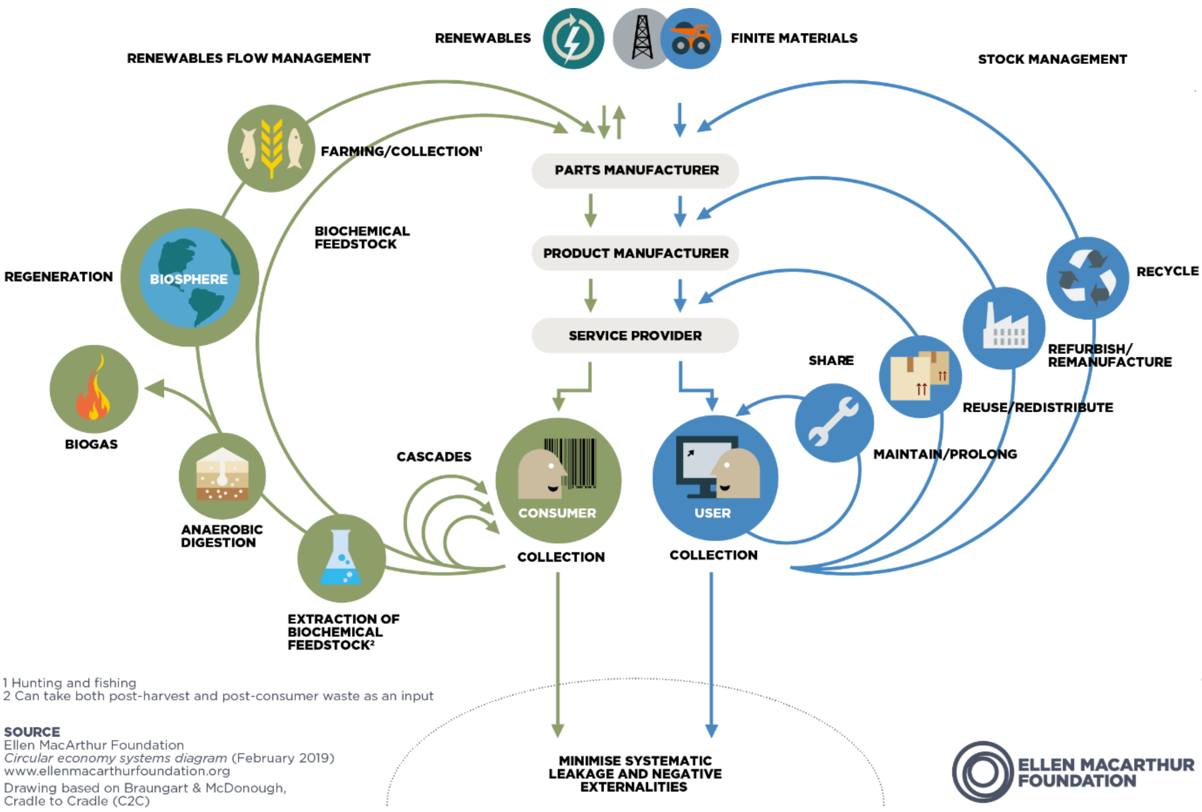

Figure 2: Circular economy butterfly diagram as developed by EMF (Ellen MacArthur Foundation, 2019)

From the systems perspective, the transition to a circular economy needs to happen at three levels: the macro level, which focuses on adjusting the industrial composition and structure of the entire economy; the meso level, which often focuses on eco-industrial parks and is also sometimes referred to as the regional level; and the micro level, which looks at individual products, enterprises, and consumers and how to increase their circularity. (Kirchherr et al., 2017, p. 224).

2.1.1. CE PRINCIPLES IN THE AEC SECTOR

Based on the abovementioned general definition, Benachio et al. (2020), defined the Circular Economy focused on the Construction Industry as

> *"The use of practices, in all stages of the life cycle of a building, to keep the materials as long as possible in a closed loop, to reduce the use of new natural resources in a construction project." (Benachio et al., 2020, p. 5)*

It is necessary to contemplate how these practices can be implemented in the AEC sector to enable the transition to a circular economy. Although "an implementation into the case-specific building full-scale evaluation is yet to be conducted" and a universal "comprehensive CE integration and methodology framework has yet to be developed" (Hossain et al., 2020b, p. 1), according to Prieto-Sandoval et al. (2018), a large number of principles that lay the foundation for the transition to the CE are described in academia. These principles can be grouped into three categories (Prieto-Sandoval et al., 2018, p. 610): principles relating to the R frameworks and sustainable design strategies, and Loop-strategies (Bocken et al. 2016).

Kirchherr et al. (2017) found that R frameworks are widely considered as the 'how-to' of CE. These frameworks express CE strategies hierarchically, considering the first R to be a priority. Several frameworks have evolved, originating from the 3R framework proposed by the Japanese Government in 2004: <u>r</u>educe with minimum use of raw materials, <u>r</u>euse with maximum reuse of products and components, and <u>r</u>ecycle with high-quality reuse of raw materials. (Mrad and Frölén Ribeiro, 2022, p. 3) The EU Construction and Demolition Waste Management Protocol (2008) introduced the fourth "R" – <u>r</u>ecovery and research has proposed alternative R frameworks that go beyond thereafter. Examples of such frameworks include the 6Rs proposed by Sihvonen and Ritola (2015) and the 9Rs suggested by van Buren et al. (2016) and Potting et al. (2017), with the latter being the most detailed, as illustrated in Figure 1. (Kirchherr et al., 2017, p. 223) However, the 4R strategies are chosen as a reference in this thesis as it is widely used in academia and comprises the underlying concept of EU regulations, such as the EU Taxonomy Regulation. The definition and an example for each 4R-core principle are presented in Table 1 (p.8).

Table 1 Definition of 4R-framework strategies according to Directive 2008/98/EC of the European Parliament and Council of 19 November 2008

<table>
<tr><th></th><th colspan="2">Definition</th><th>Building practice example</th></tr>
<tr><td>Reduce</td><td colspan="2">Comprises "measures taken before a substance, material or product has become waste, that reduce:
a) the quantity of waste, including through the re-use of products or the extension of the life span of products;
b) the adverse impacts of the generated waste on the environment and human health; or
c) the content of harmful substances in materials and products" (European Council and European Parliament, 2008, p. 8).</td><td>Increased efficiency in product manufacture and reduction of material consumption through re-design of packaging</td></tr>
<tr><td rowspan="3">Re-use</td><td colspan="2">"'re-use' means any operation by which products or components that are not waste are used again for the same purpose for which they were conceived" (European Council and European Parliament, 2008, p. 8).
Depending on whether it is possible to reuse a component with the same function, a distinction is made between ReUse and Further-Use.</td><td rowspan="3">Reuse of a reclaimed and cleaned high-fired clinker brick as a masonry block. (Hillebrandt et al., 2018, p. 59 translated by author)

Reclaimed facade bricks can be further-used as landscape architecture element, e.g. as path surfacing. (Hillebrandt et al., 2018, p. 60 translated by author)</td></tr>
<tr><td>Re-Use</td><td>Reuse or "re-purposing" is the reuse of a product without loss of value according to its original purpose. (Hillebrandt et al., 2018, p. 59 translated by author)</td></tr>
<tr><td>Further Use</td><td>"Further use is the reuse of a construction product, but not for its original purpose, since its quality can no longer be guaranteed for its original suitability. Due to the resulting loss of quality, further use means a loss of resources and is thus considered downcycling" (Hillebrandt et al., 2018, p. 60 translated by author).</td></tr>
<tr><td>Recycle</td><td colspan="2">"'recycling' means any recovery operation by which waste materials are reprocessed into products, materials or substances whether for the original or other purposes. It includes the reprocessing of organic material but does not include energy recovery and the reprocessing into materials that are to be used as fuels or for backfilling operations" (European Council and European Parliament, 2008, p. 8).
A distinction is made between recycle and downcycle, depending on whether there is a loss of value in the design-dissolving process.</td><td>A steel beam is melted down and recycled into a new steel beam of a different profile type, but without any loss of material quality. (Hillebrandt et al., 2018, p. 60 translated by author)

Flat glass is downcycled into glass blocks or profiled glass. (Hillebrandt et al., 2018, p. 60 translated by author)</td></tr>
<tr><td>Recovery</td><td colspan="2">"'recovery' means any operation the principal result of which is waste serving a useful purpose by replacing other materials which would otherwise have been used to fulfil a particular function, or waste being prepared to fulfil that function, in the plant or in the wider economy" (European Council and European Parliament, 2008, p. 8).
According to Annex II the incineration or usage as fuel or other means to generate energy are considered recovery operations (European Council and European Parliament, 2008, p. 22).</td><td>High-quality plastics can undergo several recycling processes at the same quality level before being incinerated for energy recovery. (Hillebrandt et al., 2018, p. 62 translated by author)</td></tr>
</table>

The second school of thought is based on loop strategies introduced by Bocken et al. (2016), that operationalize CE in practice (Yu, Junjan et al., 2022, p. 2): slowing the loop, closing the loop and narrowing the loop. An overview of the loop-strategies is summarized in Table 2.

Table 2 Loop strategies as CE principles in the AEC sector

Loop-strategy	**Definition**
Slowing the loop	*"Through the design of long-life goods and product-life extension (i.e. service loops to extend a product's life, for instance through repair, remanufacturing), the utilization period of products is extended and/or intensified, resulting in a slowdown of the flow of resources" (Bocken et al., 2016, p. 309).*
Closing the loop	*"Through recycling, the loop between post-use and production is closed, resulting in a circular flow of resources." (Bocken et al., 2016, p. 309)* Based on this definition recycling practices can be categorized according to their capability to replace virgin materials into: • *"Closed-loop recycling, in which the recovered material can replace virgin material indefinitely without losing its properties.* • *Semi-closed-loop recycling, where the recovered material can only replace the original virgin material to a certain extent, which is why raw materials must be added to meet quality requirements.* • *Open-loop recycling, a recycling process in which part of the material is recovered and usually used for a new purpose" (Sáez-de-Guinoa et al., 2022, p. 10).* Keeping materials and components in a closed loop translates into the reuse of building materials and deconstruction of their parts and components acting as material banks for new buildings (Benachio et al., 2020, p. 2). Furthermore, closing the material loop can be enhanced through strategies as *"reuse of materials, the C2C, eco-efficiency, zero emission, reverse logistics, regenerative design and IE"* (Ogunmakinde et al., 2021, p. 911).
Narrowing the loop	"Resource efficiency or narrowing resource flows, aimed at using fewer resources per product." (Bocken et al., 2016, p. 309)

Lastly, the sustainable design strategies (SDS) are considered the principles of the circular economy academia and by institutions such as the Ellen MacArthur Foundation (Prieto-Sandoval et al., 2018, p. 610). Accordingly, the CE is based on three design-driven approaches: eliminate waste and pollution, circulate products and materials (at their highest value) and regenerate nature. (Ellen MacArthur Foundation, 2023c). The first principle is based on the notion that "waste is a design problem". This can be addressed in the design to ensure materials are reintroduced into the economy. The reintroduction can be achieved through maintenance, sharing, reuse, and repair, refurbishment, remanufacturing, and recycling. Biological materials and food can be safely returned to the environment to fuel the production of new materials and food (Ellen MacArthur Foundation, 2023a). The second principle of the circular economy is to circulate products and materials at their highest value (Ellen MacArthur Foundation, 2023d). Designing products with the circular economy in mind is crucial for their successful circulation in either the biological or technical cycle. Products that blend technical and biological materials cannot be easily circulated, leading to waste. By designing products for easy repair, maintenance, modularity, and recyclable or biodegradable materials, they can be made with their onward path in mind (Ellen MacArthur Foundation, 2023d) Lastly, the regeneration principle aims at shifting the focus from extraction to regeneration by rebuilding the natural capital. (Ellen MacArthur Foundation, 2023b)

It is noted that the three groups have, at their core, coinciding or similar approaches. In this thesis the focus will be solely on the strategy of re-use, as it is the most prioritized in the waste hierarchy, yet less studied in research (Ginga et al., 2020, p. 16) and less implemented in building practice. Furthermore, the general term of reuse as defined in Table 1 without a distinction between re-use and further-use will be adopted.

2.1.2. LIFE CYCLE STAGES

Construction should be viewed as a cyclical process that can begin at any point in the building's life cycle (Rosen, 2020, p. 12translated by author). A common approach is to consider the life cycle stages as the four main phase production stage, construction process, the use stage and te end-of-life-stage". However, this disregards the “design process”, which is considered a fundamental phase for developing circular buildings where digital tools (DTs) play a critical role. (Çetin et al., 2021, p. 6) Therefore, in this thesis the life-cycle-stages are defined as proposed by (Çetin et al., 2021; Rosen, 2020).

Table 3 Life cycle stages in the Circular Economy

Phase	**Definition**
Pre-Use	*“The pre-use phase concerns activities that take place before buildings are occupied by users. These activities include mining raw materials or reclaiming resources from existing buildings, manufacturing building components, design, transportation, and construction or assembly.“ (Çetin et al., 2021, p. 6)*
Use	*"The use phase often constitutes the longest period of a building’s life cycle, when a significant environmental impact is created. [...] In addition, the use phase is critical to extending the lifetime of buildings and building products by activities such as repair and maintenance.” (Çetin et al., 2021, p. 6)*
Next-Use or Post-Use	*Finally, the next-use phase refers to reintroducing buildings and associated resources when they reach their end-of-use stage (Çetin et al., 2021, p. 6)*

Throughout this thesis the term “end-of-life” is frequently used for the next-use-phase as it pertains to the common terms in construction and demolition planning. However, in the envisioned CE resources are repeatedly reintroduced through reuse or recycling, without any end of life and with minimal resource input. (Çetin et al., 2021).

2.2. ARTIFICIAL INTELLIGENCE

Over the past few decades, numerous definitions of artificial intelligence (AI) have emerged. (Russell and Norvig, 2022, p. 19) In this work the definition of McCarthy (2007) is used:

> *"It is the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable.[...] Intelligence is the computational part of the ability to achieve goals in the world. Varying kinds and degrees of intelligence occur in people, many animals and some machines." (McCarthy, 2007)*

Before the aforementioned definition, the beginning of the discourse on artificial intelligence was marked by Alan Turing's, also known as the "father of computer science", influential publication, "Computing Machinery and Intelligence" in 1950, where he posed the inquiry, "Can machines think?" (IBM, 2023b) .

AI's overall concept encompasses several subfields, including machine learning and deep learning (IBM, 2023b), computer vision, robotics and sensors (Gonzalez Viejo et al., 2019), natural language processing (NLP), autonomous vehicle operating systems (UCB-UMT, 2020), etc.

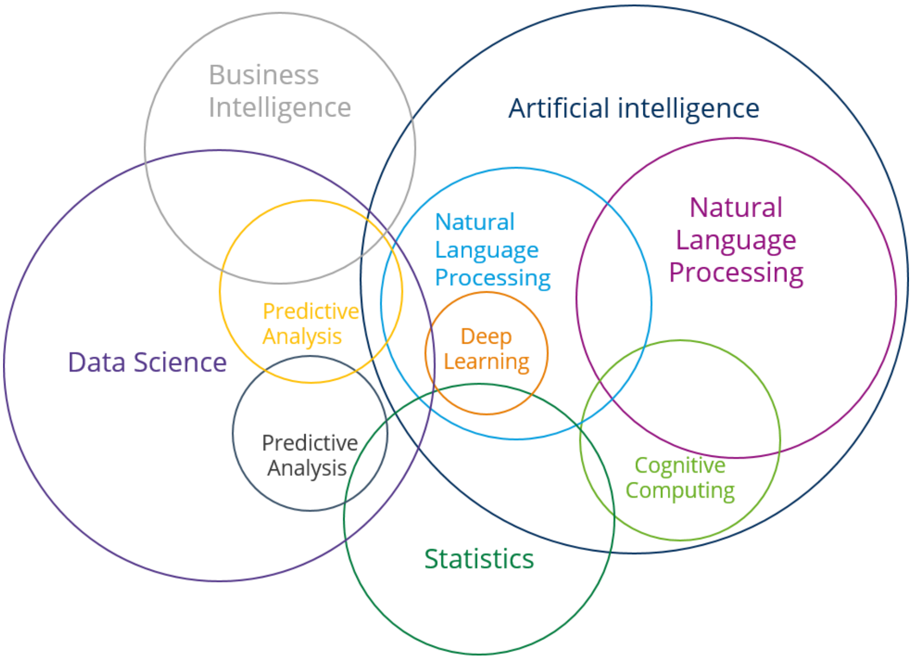

Figure 3 Overview of the different Artificial Intelligence subfields based on (Koitz-Hristov, 2020) (image by author)

The focus of this thesis is on machine learning and computer vision.

2.3. MACHINE LEARNING

Machine learning (ML) is a subfield of artificial intelligence (AI) (Kavlakoglu, 2022; Mellouk and Chebira, 2009; UCB-UMT, 2020) and was first proposed by Arthur Samuel in 1959, predicting that the programming of computers to learn from experience would eventually eliminate the need of detailed specification of problem-solving methods (Samuel, 1959, p. 535). Mitchell (1997) later defined that,

> "*a computer program is said to learn from experience* E *with respect to some class of tasks* T *and performance measure* P*, if its performance at tasks in* T*, as measured by P, improves with experience E.*" *(Mitchell, 1997, p. 2)*

In other words, machine learning is *"systematic study of algorithms and systems that improve their knowledge or performance with experience." (Flach, 2012, p. 3).* The mathematical concepts of the learning process is explained in 0 using a deep feedforward neural network.

The key distinction between conventional programming and machine learning is that programming is rule-based, i.e. it utilizes a predetermined set of rules or logic to solve problems, in contrast machine learning constructs a model or logic based on input data and responses and learns the rules autonomously. Machine learning therefore is used for problems that either are too complex for traditional approaches or have no known algorithm (Géron, 2023, p. 4). Machine learning proves advantageous in fluctuating environments. Machine learning systems can be swiftly retrained on novel data, thus maintaining up-to-date functionality. Lastly, machine learning enables the acquisition of profound insights pertaining to intricate problems and copious amounts of data. (Géron, 2023, p. 5)

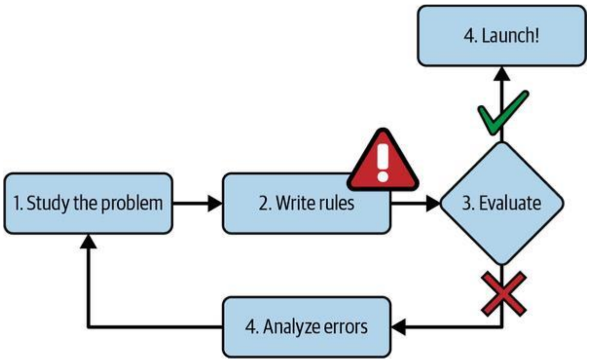

Figure 4: Traditional programming approach (Géron, 2023, p. 17)

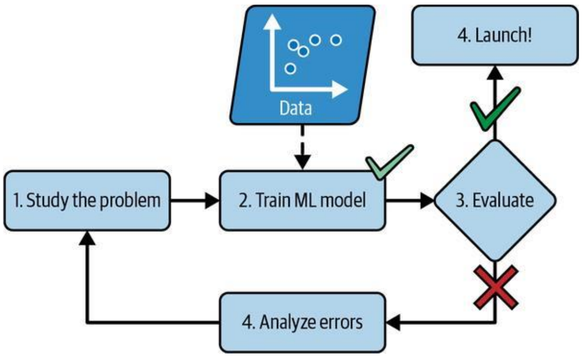

Figure 5: Machine learning approach (Géron, 2023, p. 4)

The following sections explain the experience E (2.3.1) the tasks T (2.3.2) to be performed, and the performance P (2.3.3).

2.3.1. THE EXPERIENCE E: TRAINING SUPERVISION

The learning experience of ML models is defined by the level and type of supervision received during training, i.e. the presence or absence of human influence on raw data. The main categories include supervised learning, unsupervised learning (including semi-supervised learning, self-supervised learning), and reinforcement learning (UCB-UMT, 2020).

Supervised learning is the most common form of machine learning, deep or not (LeCun et al., 2015, p. 436). In supervised learning models *"the algorithm learns on a* (fully) *labeled dataset, providing an answer key that the algorithm can use to evaluate its accuracy on training data"* (Salian, 2018). "*Fully labeled means that each example in the training dataset is tagged with the answer the algorithm should come up with on its own"* (Salian, 2018). As the target variable is known, the algorithm learns to map inputs to outputs based on the patterns observed in the training data. Supervised learning tasks include classification and regression. It is noted that some regression models can be used for classification and vice versa, e.g. logistic regression is also used for classification as it outputs a value that relates to the probability of belonging to a certain class. (Géron, 2023, p. 8)

In contrast, an *unsupervised model* presents unlabeled data which the algorithm tries to comprehend by extracting features and patterns on its own (Salian, 2018). Unsupervised learning tasks include *clustering*, *visualization algorithms*, *dimensionality reduction, anomaly detection and novelty detection*, and *association rule learning*. (Géron, 2023, p. 10) Clustering is the most common unsupervised task and involves identifying potentially meaningful clusters or groups within a set of input examples. For example, when presented with a vast collection of images sourced from the Internet, a computer vision system can detect a sizable cluster of similar images that a human observer would classify as "cats." (Russell and Norvig, 2022, p. 671) S*emi-supervised* learning uses a partially labeled data, in which a small amount of labeled data bolsters a larger set of unlabeled data (Salian, 2018). These algorithms combine unsupervised and supervised approaches, such as clustering instances and assigning them the most common label within their cluster, followed by employing supervised learning algorithms (Géron, 2023, p. 13). For example, photo-hosting services like Google Photos use unsupervised algorithms to automatically recognize individuals in photos. Once clustered, the system requires labels to identify individuals, allowing for easier searching of photos. (Géron, 2023, p. 13) *Self-supervised learning* generates a fully labeled dataset from a fully unlabeled one. For instance, by masking a small portion of each image from a large dataset of unlabeled images and training a model to recover the original image, the dataset can be labeled, enabling the use of any supervised learning algorithm. This approach is valuable for tasks like image restoration or object removal. Unlike unsupervised learning, self-supervised learning uses generated labels during training and focuses on tasks similar to supervised learning, such as classification and regression. (Géron, 2023, p. 13)

Finally, in *reinforcement learning* the algorithm learns by interacting with an environment and receiving feedback in the form of rewards or penalties. The agent learns to develop the best strategy or policy to maximize rewards over time. Notable examples include robots learning to walk and DeepMind's AlphaGo program, which analyzed millions of games and played against itself to learn its winning policy. This process is called offline learning. (Géron, 2023, p. 14)

2.3.2. THE TASK T

The machine learning task T typically refers to how a machine learning system should handle an example. An example is defined as a set of features that have been quantitatively measured from an object or event that the machine learning system is intended to process. (Goodfellow et al., 2016, p. 97) Formally, the task of supervised learning is this:

Given a training set consisting of N input-output pairs

$$(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N),$$

where each pair is generated by an unknown function $y = f(x)$, the objective is to find a function h that approximates the true function f. (Russell and Norvig, 2022, p. 671)

A non-exhaustive list of most common tasks that can be solved with machine learning includes: classification, classification with missing inputs, regression, transcription, machine translation, structured output, anomaly detection, synthesis and sampling, imputation of missing values, denoising, fate estimation or probability mass function estimation (Goodfellow et al., 2016, pp. 98–101), clustering, visualization algorithms, dimensionality reduction, association rule learning (Géron, 2023, p. 10). However, for the purpose of this paper, only classification and regression, as well as object detection and segmentation in the context of computer vision (see 2.5 Computer vision) will be addressed.

Classification

Classification is the task of assigning a class or category to a given pattern (Dreyfus, 2005, p. 33) and it *"is the most common task in machine learning"* (Flach, 2012, p. 52). In classification, the learning algorithm is typically trained to generate a function $f: R_n \rightarrow \{1, \ldots, k\}$, where $y = f(x)$ assigns an input represented by vector x to a specific category indicated by numeric code y. Alternatively, in *multi-class classification* the task may involve the output of a probability distribution over classes by function f. (Goodfellow et al., 2016, p. 98)

Regression

In this type of task, the learning algorithm aims to predict a numerical value given a specific input. The program is trained to output a function $f: R_n \rightarrow R$. While similar to classification tasks, regression tasks differ in their output formats (Goodfellow et al., 2016, p. 99). An example of regression is the prediction of the price of a house based on properties like number of bedrooms, the base area, the location, and the age of the house.

2.3.3. THE PERFORMANCE P

The abilities of a machine learning algorithm are evaluated by a quantitative measure of its performance. The performance metric P is generally tailored to the specific task being performed by the system. (Goodfellow et al., 2016, p. 101)

In classification it is common to evaluate the model's performance using accuracy, which represents the "*proportion of examples for which the model produces the correct output"* (Goodfellow et al., 2016, pp. 101–102). Equivalent information is obtained from the error rate, which represents *"the proportion of examples for which the model produces an incorrect output"* (Goodfellow et al., 2016, p. 102).

The performance of the machine learning algorithm on unseen data is of primary interest as it reflects its real-world effectiveness. To assess this, performance measures are evaluated using a separate test dataset that differs from the training data. While selecting a performance measure may appear clear-cut and objective, it can be challenging to choose one that aligns closely with the desired behavior of the system. (Goodfellow et al., 2016, p. 102) The performance measures used in this thesis include precision P, recall R and the mean average precision (mAP), and are explained in 5.2Training and Validation.

2.4. NEURAL NETWORKS (NNS)

This chapter discusses neural networks and, in the context of deep learning, particularly convolutional neural networks. These concepts underlie the practical part of the thesis and are necessary to understand the training, validation, and testing of the object detection model.

2.4.1. FROM BIOLOGICAL TO ARTIFICIAL NEURONS

The history of neural networks dates back to 1943 when McCulloch and Pitts published the landmark paper *"A Logical Calculus of Ideas Immanent in Nervous Activity"*[1] on neurons and Boolean logic. In 1958, Frank Rosenblatt developed the perceptron which introduced weights to the equation. (IBM, 2023c) Key events that led to the evolution of neural networks include Paul Werbos' 1974 observation of backpropagation's application in neural networks and Yann LeCun's 1989 paper that demonstrated the use of constraints in backpropagation to train algorithms, successfully recognizing hand-written zip code digits. (IBM, 2023c)

[1] Warren S. McCulloch and Walter Pitts, "A Logical Calculus of the Ideas Immanent in Nervous Activity", The Bulletin of Mathematical Biology 5, no. 4 (1943): 115–113.

The idea of artificial neural networks (ANNs) has been influenced by the recognition that biological learning systems are constructed from highly intricate networks of interconnected neurons. Biological neurons behave simply but are organized in a vast network. With each neuron connected to thousands of others, they can perform complex computations, often organized in consecutive layers. (Géron, 2023, p. 280)

Similarly, a neuron *„is a nonlinear, parameterized, bounded function*" (Dreyfus, 2005, p. 18) and a neural network "*is the composition of the nonlinear functions of two or more neurons*" (Dreyfus, 2005, p. 19). Neuronal networks (NNs) are typically represented by a network diagram (Goodfellow et al., 2016; Hastie et al., 2009, p. 390) as seen in Figure 6.

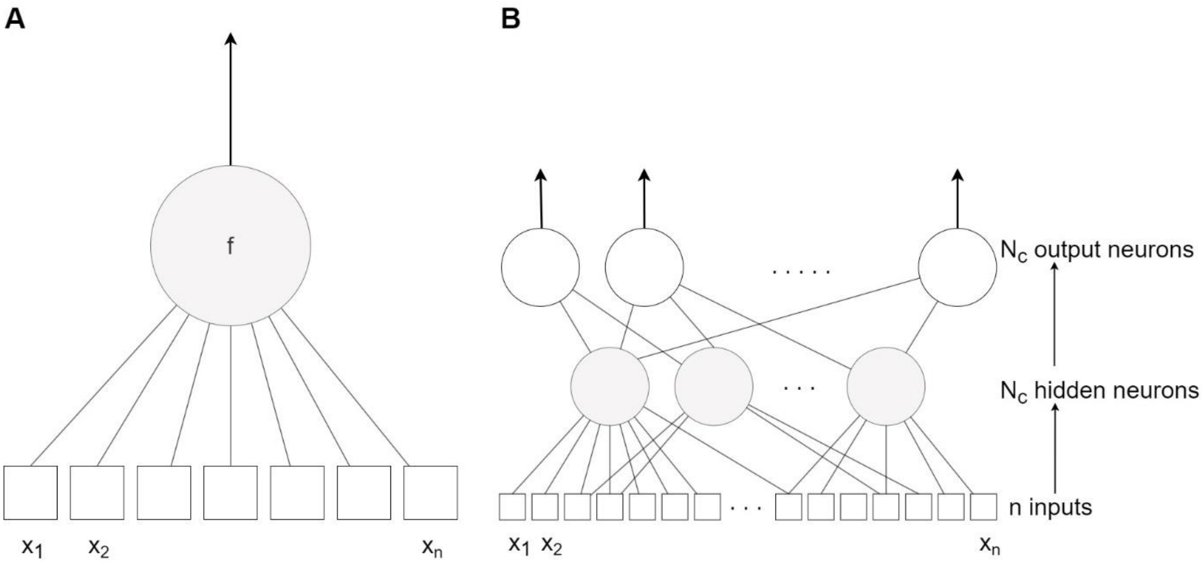

Figure 6 Network diagram of (A) a single input neuron and (B) a neural network with n inputs, a layer of hidden neurons, and Nc output neurons.
The network consists of layers of neurons (nodes or units), which include an input layer, one or more hidden layers, and an output layer. The neurons are connected to each other and have an assigned weight and threshold. When the output of a particular node exceeds the specified threshold value, it becomes activated and sends information to the next layer in the network. However, if the output is below the threshold, no data is transmitted to the subsequent layer of the network (IBM, 2023a). Illustration adapted from (Dreyfus, 2005, p. 18), image by author.

There are two main classes of NNs: feedforward and recurrent networks (or feedback networks). (Dreyfus, 2005, p. 19) Feedforward networks are NNs where information flows in one direction, from the input layer through intermediate layers to the output layer, without any feedback connections. On the other hand, recurrent networks, include feedback connections where outputs are fed back into the network, allowing information to be propagated in a loop-like manner. (Goodfellow et al., 2016, p. 164) In the context of this thesis, however, only feedforward NNs are relevant.

2.4.2. FEEDFORWARD NETWORKS

Feedforward neural networks (FNNs) are composed of multiple functions. The composition of the functions varies, with chain structures being the most common structures in FNNs. For example, three functions $f^{(1)}$, $f^{(2)}$, and $f^{(3)}$ connected in a chain form

$$f(x) = f^{(3)}\left(f^{(2)}\left(f^{(1)}(x)\right)\right)$$

In these structures, each function f represents a *layer* in the network. The *depth* of the model is determined by the length of this chain. The first layer is the *input layer*, while the final layer is the *output layer*. The behavior of the intermediate layers, known as *hidden layers*, do not directly correspond to the training data. Instead, the learning algorithm determines how to use these hidden layers to approximate the desired output. (Goodfellow et al., 2016, pp. 164–165). The mathematical representation of feedforward networks can best be described using the perceptron.

Perceptron: Learning Mathematics

The perceptron is one of the simplest NN architectures and can be considered a feedforward neural network with zero hidden layers. It was invented in 1957 by Frank Rosenblatt and is based on an artificial neuron called threshold logic unit (TLU) or linear threshold unit (LTU) (Géron, 2023, p. 284).

The inputs of a neuron are commonly referred to as its *variables*, while its output corresponds to its value. In the perceptron architecture TLUs operate on numerical inputs and produce weighted sums z of these inputs:

$$z = w_1 x_1 + w_2 x_2 + \cdots + w_n x_n = x^{\intercal} w$$

This sum is then passed through the activation function, which in the perceptron is a step function step(z), to generate an output (Géron, 2023, p. 284):

$$h_w(x) = step(z) \qquad \textit{Equation 2-1}$$

Perceptrons commonly utilize the Heaviside step function as the primary step function $step(z)$ or alternatively, the sign function (Géron, 2023, p. 285).

$$heaviside(z) = \begin{cases} 0 \; if \; z < 0 \\ 1 \; if \; z \geq 0 \end{cases}; \qquad \textit{Equation 2-2}$$

$$sgn(z) = \begin{cases} -1 \; if \; z < 0 \\ 0 \; if \; z = 0 \\ +1 \; if \; z > 0 \end{cases} \qquad \textit{Equation 2-3}$$

A single TLU performs linear binary classification by computing a weighted sum of the inputs (see). If the sum exceeds a threshold, it outputs the positive class; otherwise, it outputs the negative type.

A perceptron consists of a single layer of TLUs, where each TLU is fully connected to all inputs known as a *fully connected* or dense layer. Input neurons in the perceptron pass the inputs as they are and form the input layer (see Figure 7). An additional bias feature ($x_0 = 1$) is typically included and represented by a bias neuron that constantly outputs 1. (Géron, 2023, p. 285)

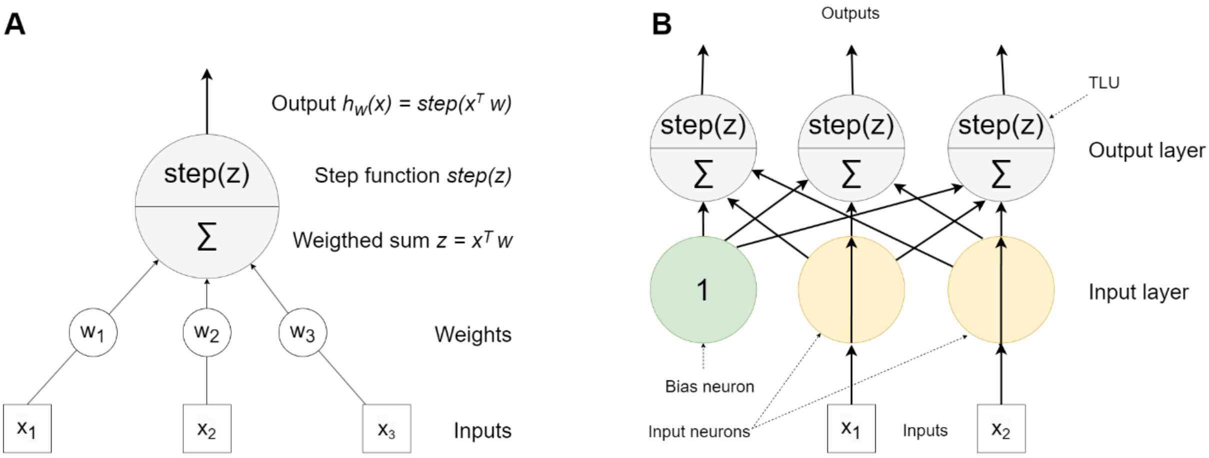

Figure 7 (A) Architecture of a Threshold Logic Unit (TLU) and (B) Architecture of a Perceptron with two input neurons, one bias neuron and three output neurons, illustration adapted from (Géron, 2023, p. 284), image by author.

The output of a layer of artificial neurons for multiple instances is simultaneously computed using Equation 2-4 (Géron, 2023, p. 286):

$$h_{W,b}(X) = \Phi(XW + b) \qquad \textit{Equation 2-4}$$

Where

X represents the input feature matrix, with rows representing instances and columns representing features.

W is the weight matrix, that contains the connection weights, excluding those from the bias neuron. It has rows for each input neuron and columns for each artificial neuron in the layer

b is the bias vector containing the connection weights between the bias neuron and the artificial neurons, with each bias term corresponding to an artificial neuron.

ϕ is the activation function that determines the output of artificial neurons. For TLUs its usually a step function (Géron, 2023, p. 286)

The training of a perceptron involves a training algorithm that implements a variant of Hebb's[2] by considering the prediction error made by the network. This learning rule strengthens the connections that aid in reducing error. During training, the perceptron

[2] The Hebb's rule or Hebbian theory was formulated in 1949 by neuropsychologist Donald Hebb in his publication "The Organization of Behaviour" (Hebb (2005) according to which frequent triggering of one biological neuron by another leads to a strengthening of the connection between them.

processes one training instance at a time and makes predictions. If an output neuron produces an incorrect prediction, the connection weights from the inputs that would have contributed to the correct prediction are reinforced. The rule is expressed in Equation 2-5 (Géron, 2023, pp. 286–287):

$$w_{i,j}^{(next\ step)} = w_{i,j} + \eta\left(y_j - \hat{y}_j\right)x_i \qquad \textit{Equation 2-5}$$

The variables in this equation are as follows:

$w_{i,j}$ represents the connection weight between the i-th input neuron and the jth output neuron.

x_i denotes the ith input value of the current training instance.

$\hat{y}_j$ is the output of the j-th output neuron for the current training instance.

y_j represents the target output of the j-th output neuron for the current training instance.

η represents the learning rate. (Géron, 2023, p. 287)

As the decision boundary of each output neuron is linear, the perceptron cannot learn complex patterns. Furthermore, unlike logistic regression classifiers, perceptrons do not provide class probabilities but make predictions based on a hard threshold. Hence, perceptrons are unable to solve certain simple problems, such as the Exclusive OR (XOR) classification problem. These limitations are overcome by using multiple perceptrons stacked together generating a multilayered perceptron (MLP) (Géron, 2023, p. 288).

Deep Feedforward Networks

A MLP consists of an input layer, one or more hidden layers of TLUs, and an output layer of TLUs (Géron, 2023, p. 289). Due to the architecture of *"multiple layers of simple, adjustable computing elements"* (Russell and Norvig, 2022, p. 44), MLPs are also known as *deep feedforward networks* or *feedforward neural networks* and are considered fundamental models in deep learning (Goodfellow et al., 2016, p. 164).

The limitation of linear models in representing nonlinear functions of x is addressed by applying the linear model to a transformed input $\varphi(x)$ instead of x itself. The nonlinear function φ provides *"a set of features that describe x"*, or offers *"a new representation for x"* (Goodfellow et al., 2016, pp. 165–166). In deep learning, the nonlinear function φ is learned. In this approach, the model is:

$$y = f(x;\ \theta, w,) = \varphi(x;\ \theta)^{\intercal} w \qquad \textit{Equation 2-6}$$

with φ defining a hidden layer (Goodfellow et al., 2016, p. 166). At each hidden layer, a non-linear transformation is performed on the weighted sum of the outputs from the units in the layer below (LeCun et al., 2015, p. 437). The parameters θ are used to learn φ from a broad class of functions and the parameters w map from $\varphi(x)$ to the desired output (Goodfellow et al., 2016, p. 166). Currently, *"the most popular non-linear function is the rectified linear unit (ReLU), which is simply the half-wave rectifier f(z) = max(z, 0)"* (LeCun et al., 2015, p. 438).

In deep neural networks, the c*ost function* (also *loss function*, *objective function, or criterion)* quantifies the error or discrepancy between the predicted output of the model and the actual target output. The goal of training these networks is to minimize the prediction error, addressed by optimization algorithms that search for the optimal set of parameter values θ or *weights* that minimize the cost function (Goodfellow et al., 2016, p. 166). Mathematically, a local minimum in a function is determined by analyzing the derivative of the loss function (Goodfellow et al., 2016, p. 81). For functions with multiple inputs, the gradient is calculated. The gradient is the derivative for a function $g(x)$ with the input vector x expressed as a vector $\nabla x\ g(x)$ containing all the partial derivatives of g with respect to each component of x. (Goodfellow et al., 2016, p. 82) In deep learning the gradient is computed using back-propagation, while learning is performed using other algorithms, such as stochastic gradient descent (Goodfellow et al., 2016, p. 200). These two concepts are briefly discussed below.

Backpropagation

Backpropagation is a specific algorithm that efficiently computes the gradients in a deep feedforward network, such as the object detection model used in 5 Machine Learning Pipeline. It calculates the gradients of the loss function with respect to the weights of each layer in the network by recursively applying the chain rule for derivatives (LeCun et al., 2015, p. 438).The process involves two main steps: forward propagation and backward propagation.

During *forward propagation*, the input data is fed into the network, and the activations of each layer are computed by applying the non-linear transformation function to the weighted sum of inputs resulting in the output layer providing the predicted output of the model according to Equation 2-6.

Next, during backward propagation, the error or loss between the predicted output and the target output is calculated. The core concept is to compute the gradient (or derivative) of the cost function with respect to the input of a module by working backwards from the gradient with respect to the output of that layer (or the input of the subsequent layer) using the chain rule (LeCun et al., 2015, p. 438) By iteratively applying the backpropagation equation, gradients can be propagated through all the modules in a deep network. Starting from the top output layer, where the network generates predictions, moving downwards to the bottom where the external input is received. Once these gradients have been calculated, it becomes straightforward to compute the gradients with respect to the weights of each individual module (LeCun et al., 2015, p. 438).

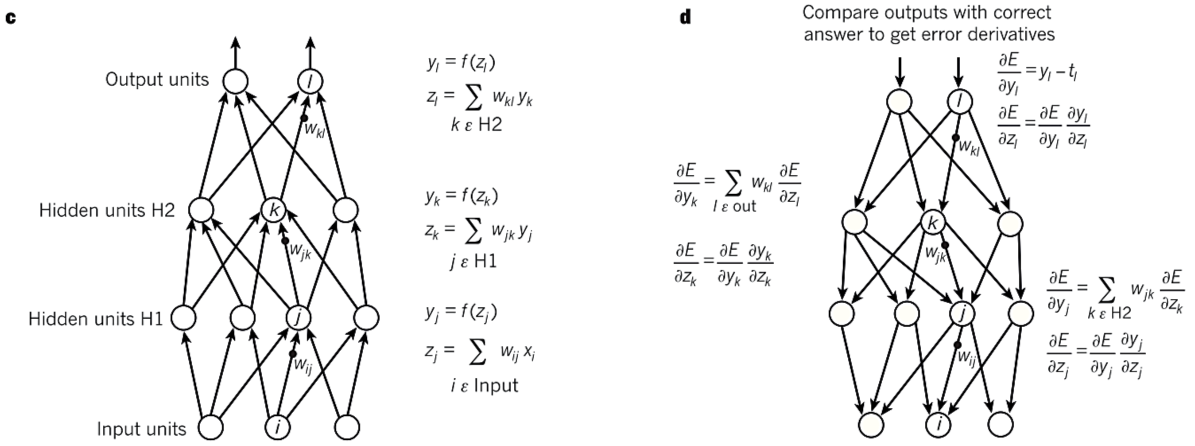

Figure 8: Multi-layer neural networks: c) forward and d) back-propagation (LeCun et al., 2015, p. 437)

Stochastic Gradient Descent

The majority of deep learning algorithms rely on an optimization algorithm called the Stochastic Gradient Descent (Goodfellow et al., 2016, pp. 96–97), which is an extension of the Gradient Descent (Goodfellow et al., 2016, p. 149).

The Gradient Descent is an optimization algorithm that iteratively adjusts parameters to minimize a cost function by following the direction of the steepest slope. It measures the local gradient of the error function to the parameter vector θ, moves in the direction of descending gradient in learning steps, and iteratively adjusts θ to minimize the cost function until convergence (Géron, 2023, p. 118). The learning rate (LR) in Gradient Descent determines the size of each step taken during parameter updates, influencing the convergence speed towards a minimum. The LR is one of the most important hyperparameters in the training and fine-tuning of machine learning models (see 5.2.2 Training Configuration).

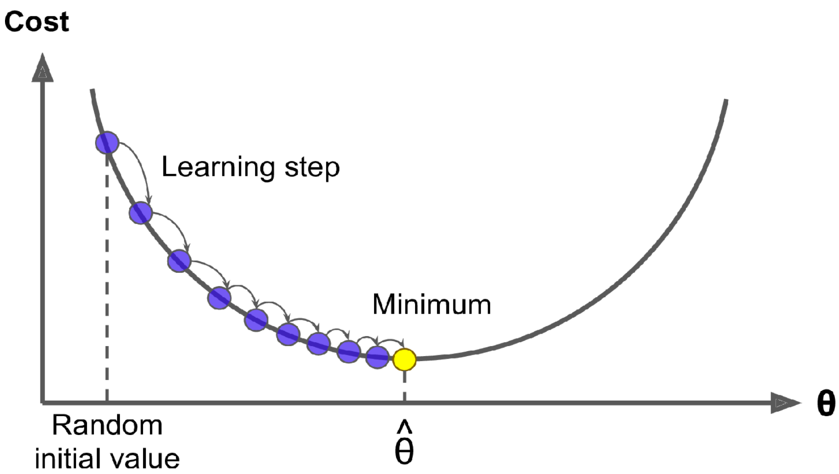

Figure 9: Gradient Descent (Géron, 2023, p. 118)

One challenge in machine learning is the trade-off between the need for large training sets to achieve good generalization and the computational expense associated with processing them (Goodfellow et al., 2016, p. 149). However, (Batch) Gradient Descent uses the whole training set (in one Batch) to compute the gradients at every step, making it very slow (Géron, 2023, p. 124). In stochastic gradient descent (SGD), on the other hand, the input vector is shown for a few examples, the outputs and errors are computed, the average gradient is calculated, and the weights are adjusted accordingly. This process is repeated with small sets of examples (mini batches) until the average of the loss function no longer decreases. Despite being a simple procedure, SGD often achieves good weight values quickly compared to more complex optimization techniques. The system's performance is then evaluated on a separate set of examples called a test set to assess its ability to generalize and produce meaningful outputs for unseen inputs (LeCun et al., 2015, p. 437).

2.4.3. CONVOLUTIONAL NEURAL NETWORKS

A Convolutional Neuronal Network (CNN or ConvNets) is a class of multilayered feedforward neural networks designed to detect complex features in data (QuinnRadich, 2023) *"that come in the form of multiple arrays, for example a colour image composed of three 2D arrays containing pixel intensities in the three colour channels"* (LeCun et al., 2015, p. 439). The need for manual extraction is replaced by automatic feature extraction/identification, which renders CNN models highly accurate and efficient for many tasks in computer vision, e.g., object recognition and classification (see 2.5 Computer vision) (Darko et al., 2020, p. 8). ConvNets leverage the properties of natural signals with four key ideas: local connections, shared weights, pooling, and the utilization of multiple layers (LeCun et al., 2015, p. 439).

The typical ConvNet architecture consists in sequential stages, with the initial stages comprising convolutional and pooling layers. The output of convolutional layers in a neural network consists of feature maps, which are 2D representations obtained either from the previous layer or by applying specific filters to an input image (Géron, 2023, p. 448). Each unit (or neuron) in a convolutional layer corresponds to a specific location in the feature map and is connected to local patches in the previous layer through a filter bank, a set of weights (LeCun et al., 2015, p. 439). In the convolutional layer, each unit applies a convolution operation to its local input patch using the corresponding filter bank. It involves applying a non-linear function, such as ReLU, to the weighted sum and passing the output to the next layer. Each feature map shares the same filter bank, while different feature maps in a layer use different filter banks. (LeCun et al., 2015, p. 439)

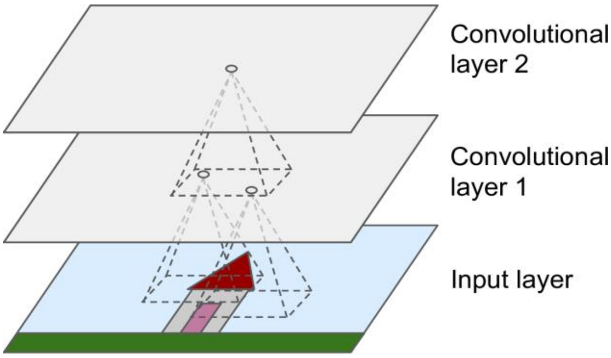

Figure 10: Convolutional layers with receptive fields of a ConvNet (Géron, 2023, p. 448)

The local patches of two neurons in an input layer may overlap. The amount of overlap between patches is determined by the stride parameter used during the convolution operation. If the stride is set to a value less than the patch size, such as stride=1, the patches will overlap. This means that neighboring patches will share some common elements, allowing the network to capture more fine-grained spatial information and potentially improve the network's ability to detect smaller features. On the other hand, if the stride is set to a value greater than the patch size, such as stride=2, the patches will have a gap between them, resulting in less overlap. This can reduce the computational cost and memory requirements of the network but may lead to a coarser representation of the input data. (Géron, 2023)

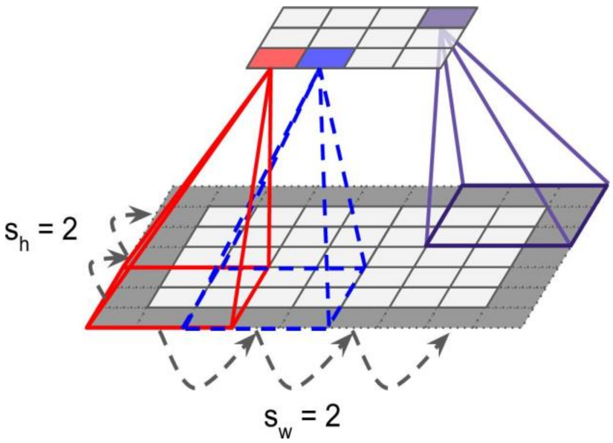

Figure 11: Stride of local patches (Géron, 2023, p. 450)

This architecture is motivated by the high correlation of local groups of values that form distinctive and easily detectable local motifs in array data like images. These local motifs are invariant to location, meaning that *"if a motif can appear in one part of the image, it could appear anywhere"* (LeCun et al., 2015, p. 439). This allows units at different locations to share weights and detect patterns across the array. The filtering operation performed by a feature map is a discrete convolution (LeCun et al., 2015, p. 439). Convolutional operations on learned features with input data simultaneously learn and extract optimal, effective, and highly intricate features for directly recognizing visual patterns from raw data (Darko et al., 2020, p. 13).

While a convolutional layer detects local conjunctions of features from the previous layer, the pooling layer merges semantically similar features by coarse graining their positions. Common pooling units compute the maximum local patch of units in one or few feature maps (see Figure 11). Neighboring pooling units reduce the dimension of the representation and create an invariance to small shifts and distortions by taking input from patches that are shifted by more than one row or column.

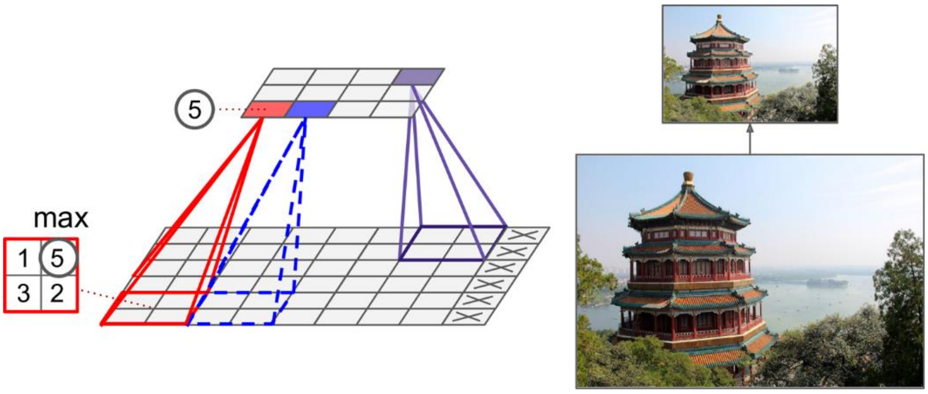

Figure 12: Pooling Layer in a ConvNet (Géron, 2023, p. 457)

In common ConvNet architectures, multiple stages of convolution, non-linearity, and pooling are stacked, followed by additional convolutional and fully connected layers. Backpropagation through a ConvNet is straightforward, enabling the training of all weights in the filter banks (LeCun et al., 2015, p. 439). Deep neural networks leverage natural signals' compositional hierarchy property, where lower-level features are formed by combining lower-level ones. This applies to images, where local edge combinations form motifs, motifs combine to create parts, and parts assemble into objects. Pooling ensures that representations remain consistent even when elements in the previous layer vary in position and appearance (LeCun et al., 2015, p. 439).

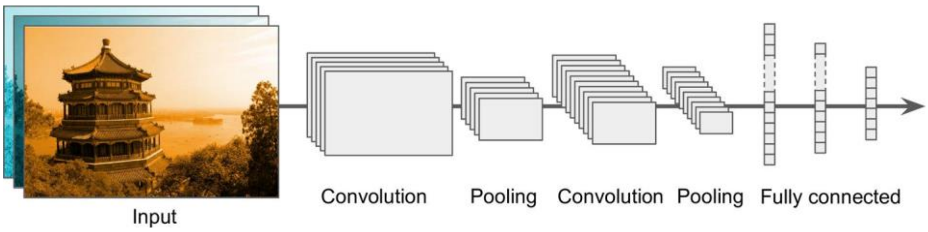

Figure 13: Typical ConvNet architecture (Géron, 2023, p. 461)

In conclusion, the theoretical concepts explored in this chapter lay the groundwork for training, validating, and testing the object detection model in Chapter 5, Machine Learning Pipeline. The chosen object detection model, YOLO (You Only Look Once), utilizes a ConvNet as its backbone architecture, and during training, the hyperparameters presented here are fine-tuned.

2.5. COMPUTER VISION

Computer vision is a subfield of artificial intelligence that uses deep learning models and other methods to enable computers to recognize and understand visual information, including objects, scenes, and actions in images or videos. Computer vision encompasses a wide range of subfields, each focusing on specific tasks and techniques that range from reproducing human visual abilities, such as recognizing faces, to creating entirely new categories of visual abilities.

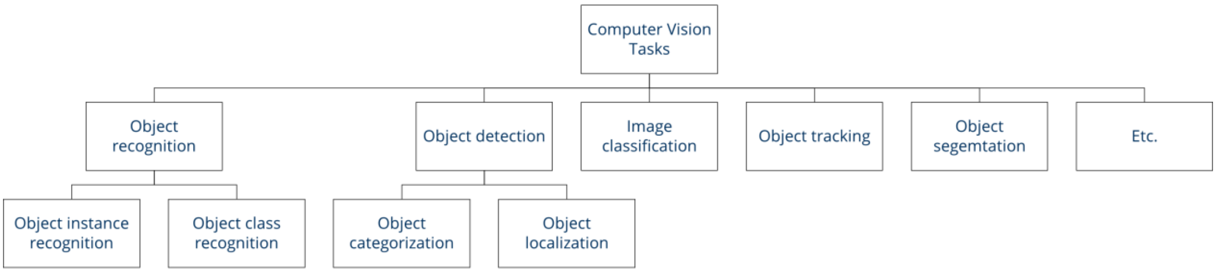

Figure 14 Computer vision tasks (image by author)

For the scope of this work, which includes the detection of reusable components in 360° images, only object detection is relevant. The concept of segmentation will only briefly be discussed here for completeness, as it plays only a minor role in the rest of the thesis.

2.5.1. OBJECT DETECTION

Object detection is a problem in the field of computer vision. It is considered one of the most fundamental and challenging problems in computer vision, as it requires the algorithm to accurately detect objects within an image, even when they appear in different orientations, scales, and lighting conditions (Liu et al., 2018b).

Object detection involves two tasks: object categorization and object localization. (Zhang et al., 2013, p. 4). Object localization includes localizing objects accurately in the image to separate them from the background and determining the *"extents of all the objects that are found present"* (Zhang et al., 2013, p. 4). Object categorization refers to recognizing objects and determining whether any instances of defined categories are present (Zhang et al., 2013, pp. 2–3).
Generally, there are two types of object detection: detection of specific instances and detection of broad categories (Liu et al., 2018a, p. 1).Object instance detection can be considered a matching problem, as it aims to detect instances of a particular object (Liu et al., 2018a), such as Konrad Zuse, the family's dog or the Brandenburg Gate. On the other hand, object class detection focuses on detecting previously unseen instances of pre-defined categories. Object class detection is also known as category-level or generic object detection. This second task is more challenging due to the large number of categories and

intra-category appearance variations caused by differences in color, texture, shape, and imaging conditions. Additionally, objects in real-world scenes are often partially occluded and accompanied by similar-looking background structures, making accurate location and separation from the background critical.

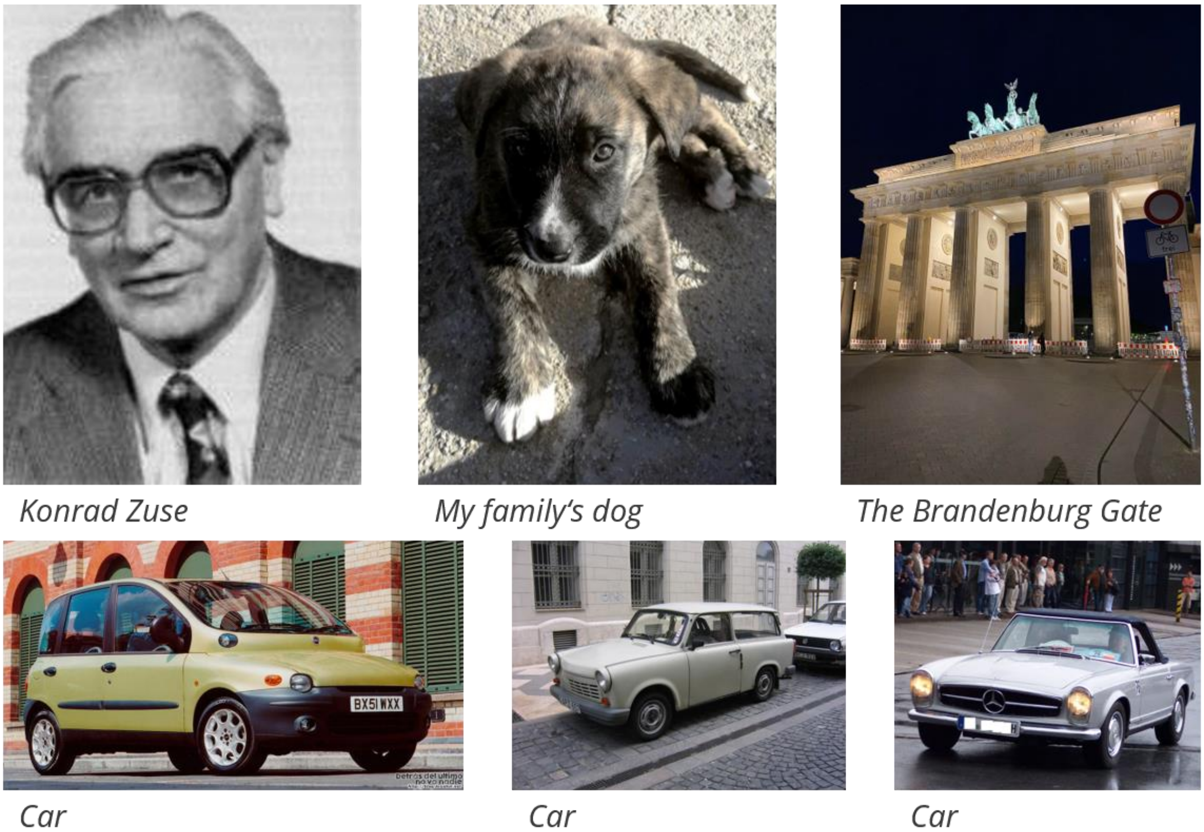

Figure 15 Examples of specific and generic object detection.
Specific object detection includes localizing instances of a particular object (upper row), as well as generalizing to generic object categories (lower row). Images by author or used under Creative Commons Licence.

Object recognition has evolved from geometric representations to statistical classifiers (such as Neural Networks, SVM, etc.) based on appearance features. In 2012 Krizhevsky et al. proposed a Deep Convolutional Neural Network (DCNN) called AlexNet which achieved record-breaking image classification accuracy in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). CNNs have been used for object detection and localization since the 1990s. However, deeper CNNs (DCNNs) have led to significant improvements in detecting general object categories. This shift occurred when successful DCNN applications in image classification were applied to object detection, resulting in the milestone Region-based CNN (RCNN) detector by Girshick et al. in 2014. DCNNs heavily rely on vast training data and large networks with millions or billions of parameters. The goal now is to build general-purpose object detection systems that approach human-level performance on thousands of categories, still needs to be solved (Liu et al., 2018a, pp. 5–6).

Before deep learning, traditional object detection models followed a three-staged approach: informative region selection, feature extraction, and classification (Zhao, Z. Q. et al., 2019, p. 3212). In the information region selection stage, the sliding-window-method was commonly used: Here, a fixed-size rectangular window slid across the image, applying a classifier or detector on each window (Felzenszwalb et al., 2010, p. 1628) to determine if it contains the target object or class. Feature extraction algorithms were then used to generate semantic and robust image representations, followed by classification algorithms serving as the classifier (Li et al., 2023, p. 509). However, the sliding-window method often leads to multiple detections of the same object at slightly different positions necessitating post-processing techniques like Non-Maximum-Suppression (NMS) to eliminate redundant or overlapping bounding boxes[3] (Géron, 2023, p. 486) Despite its effectiveness, the sliding-window method is computationally expensive (Géron, 2023; Liu et al., 2018a; Zhao, Z. Q. et al., 2019), leading to the development of more efficient object detection frameworks such as the region based (two staged) and unified (one stage) frameworks.

In a two-stage framework, in the first stage, a deep fully convolutional network is responsible for generating category-independent region proposals from an image, and features are extracted from these regions using a CNN. In the second stage, a region-based CNN (R-CNN) detector uses proposed regions and the feature map as inputs (Chou et al., 2020, p. 838). It classifies proposals and refines their bounding boxes using category-specific classifiers to determine the category labels of the proposals. (Liu et al., 2018a, p. 10)

Conversely*, one-stage or unified object detection pipelines* are a type of architecture that utilize a single CNN to directly predict both class probabilities and bounding box offsets from full images, without the need for region proposal generation or post-classification feature resampling (Zhao, Z. Q. et al., 2019, p. 3214). The model divides the image feature into grids and predicts B bounding boxes with confidence scores for each grid cell. It also predicts C conditional class probabilities based on the presence of an object. During testing, class-specific confidence scores are obtained by combining the conditional class probabilities and individual box confidence predictions. These scores represent the likelihood of a class appearing in the box and the accuracy of the predicted box (Chou et al., 2020, p. 838). This monolithic approach *"regards object detection as a regression or classification problem"* (Chou et al., 2020; Zhao, Z. Q. et al., 2019, p. 3214) and encapsulates all necessary computations within a single network (Liu et al., 2018a, p. 13). The one-stage object detection is the underlying approach of this thesis' YOLO model and therefore particularly relevant.

[3] Bounding boxes refer to axis-aligned rectangles that tightly bound the object, that coarsely defines the spatial location and extent of that object Liu et al. (2018a).

2.5.2. SEGMENTATION

"Image segmentation is a commonly used technique in digital image processing and analysis," and computer vision "*to partition an image into multiple parts or regions, often based on the characteristics of the pixels in the image"* (MathWorks, 2023). In segmentation, several related problems are distinguished, *"namely semantic segmentation (per-pixel class labeling), instance segmentation (accurately delineating each separate object), (and) panoptic segmentation (labeling both objects and stuff)"* (Szeliski, 2022, p. 307). Semantic segmentation is a detection approach "*in which each pixel is labeled with the class of its enclosing object or region"* (Long et al., 2014, p. 1). On the other hand, *instance segmentation* is the task of finding all of the relevant objects in an image and producing pixel-accurate masks for their visible regions (Szeliski, 2022, p. 311). Instance segmentation can therefore be considered a combination of both object detection and segmentation. (Yi et al., 2019, p. 230) Simplified, semantic segmentation classifies pixels into semantic categories (e.g., "stuff"), while instance segmentation associates pixels with individual object instances. Combining both results in *panoptic segmentation* where all objects are segmented and "stuff" is labeled. (Szeliski, 2022, pp. 312–313)

Figure 16 Example of semantic segmentation (Géron, 2023, p. 492)

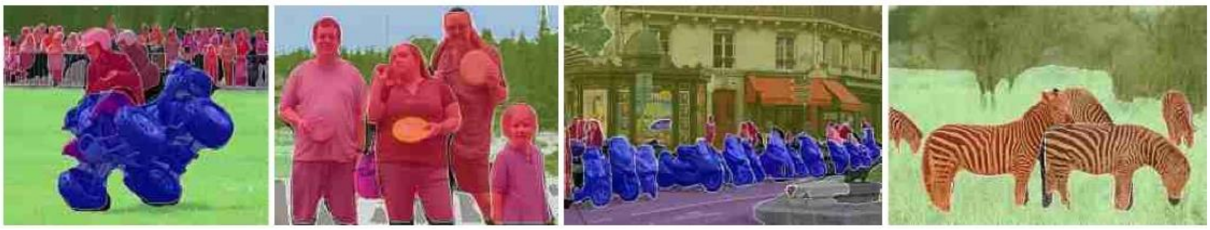

Figure 17: Panoptic Segmentation results, adapted from (Kirillov et al., 2019, p. 2)

The remainder of this thesis focuses on generic *object detection* techniques that use CNN backbone structures, which are further explored in Chapter 4.2.2, Analysis of techniques for identifying components.

2.6. 360° IMAGING

The technique of 360° images, also known as panoramic, omnidirectional or 360° images involves capturing omnidirectional views of the surrounding environment to create a virtual space that replicates the viewpoints surrounding the user (Eiris and Gheisari, 2019). These images are generated using specialized devices (360 cameras) that use multiple lenses or a single wide-angle lens along with advanced stitching algorithms to seamlessly merge the captured images or videos into a spherical or panoramic view. This involves constructing an equirectangular projection in a two-dimensional plane. Similar to map projections, the algorithms are used to systematically transform the 2D plane into a spherical, cylindrical, or cubic representation, and vice versa. (Eiris and Gheisari, 2019, p. 438)

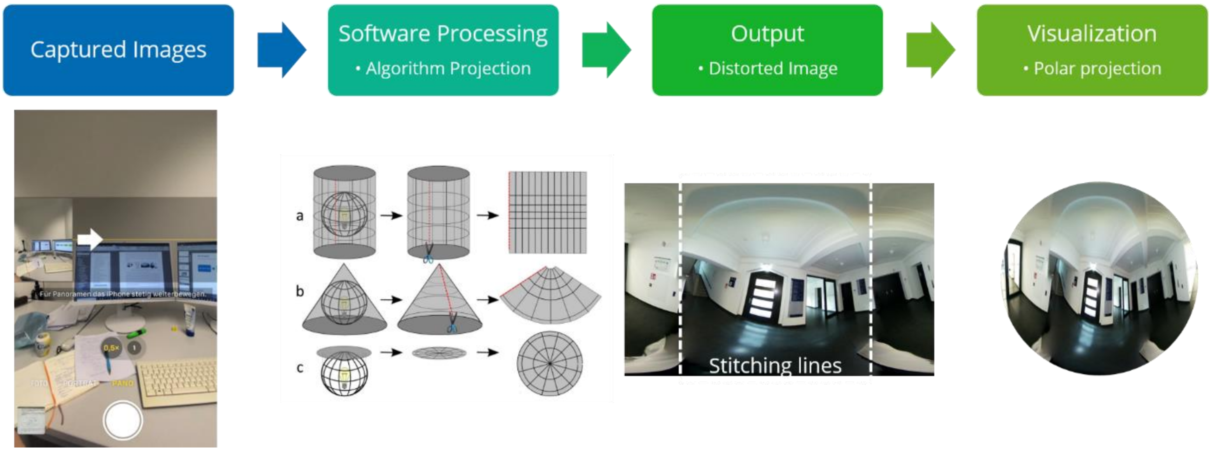

Figure 18: 360° Panoramic Development Process.
Adapted from (Eiris and Gheisari, 2019, p. 438), image by author.

In recent years, 360 cameras have become more popular (Chou et al., 2020; Eiris and Gheisari, 2019; Li et al., 2023; Su and Grauman, 2017; Zhao, P. et al., 2019) for several reasons. First, they are *"part of the rising trend of virtual reality (VR) and augmented reality (AR) technologies"* and are thought to be *"increasingly influential for wearable cameras, autonomous mobile robots, and video-based security applications"* (Su and Grauman, 2017, p. 1). Furthermore, they are particularly interesting for computer vision because of the rich contextual information provided by their large field-of-view (FOV) (Li et al., 2023, p. 508). And lastly, the availability of 360° cameras on the commercial market contributes to their popularity (Barazzetti et al., 2018, p. 69). Table 4 shows some of the sensors with their average price in May 2023.

In the context of construction, 360° images have been used for "accurate metric reconstructions" (Barazzetti et al., 2018, p. 69), for safety-training applications to enhance trainees' hazard-identification (Eiris et al., 2018) and, together with Building Information Modeling (BIM) and photogrammetry aided by an Unmanned Aerial System (UAS) "for outdoor and indoor visual monitoring of construction progress" (Barbosa et al., 2022). This aligns with Eiris and Gheisari (2019), who discovered that in the Construction field, researchers have utilized 360° panoramas to depict real-world job sites that are remote, inaccessible, or unsafe, and identified three categories of applications: Interactive Learning, Reality Backdrop to Augmented Information, and Visualize Safe and Unsafe Situations (Eiris and Gheisari, 2019, p. 436). Recently, they are gaining popularity in the as-built documentation, so that construction-specific hardware, such as the 360 helmet camera from Openexperience used in this work or Matterport360, are being developed.

Table 4 Selection of commercial 360° cameras (as of May 2023)

Producer	Name	Product type	Price	Source
Rollei	CMOS 2	Portable Camera	109,99 €	https://www.mediamarkt.de/
Samsung	Gear 360 (2. Generation)	Portable Camera	112,99 €	https://www.360gradkamera.de/
Insta360	Nano	Portable Camera	223,55 €	https://www.360gradkamera.de/
Ricoh	Theta S	Portable Camera	224,75 €	https://www.360gradkamera.de/
Insta360	One X	Portable Camera	459,00 €	https://www.360gradkamera.de/
GoPro	Gopro Max 360	Portable Camera	499,99 €	https://www.mediamarkt.de/
Insta360	ONE X2	Portable Camera	529,99 €	https://www.mediamarkt.de/
DJI	Mini 2 SE Fly More Combo	Quadrocopter	559,00 €	https://www.conrad.de/
Garmin	VIRB360	Portable Camera	699,00 €	https://www.garmin.com/de-DE/

Spherical images were, in some cases, found to be a better choice than traditional or fisheye images. For example, Brazzetti et al. (2028) found 360° cameras outperforming conventional approaches in the survey of long and narrow spaces, as well as interior areas like small rooms. Furthermore, the generation time also gives 360° cameras increased competitiveness: In the Barazzetti et al. (2018) practice example, data collection took only a few minutes with the 360 camera against several hours required by a laser scanner (Barazzetti et al., 2018, pp. 72–74). This aligns with Gheisari and Subramanian, who additionally found photogrammetry based on 360° images would "be an appropriate technique in applications where less level of accuracy would be sufficient" (Gheisari and Subramanian, 2019) such as in deconstruction planning.

3 STATE OF THE ART

In this chapter the status quo in research and practice is presented. First, the state-of-the-art research on the implementation of CE in the BE is analyzed and a review on successful circular building projects is conducted. Second, successfully implemented projects and case studies are considered. Furthermore, CE-enabling digital technologies, focusing on machine learning and artificial intelligence are researched.

3.1. METHODOLOGY

The chosen method is the systematic literature review (SLR)(Briner and Denyer, 2012, p. 112). Here, the protocol for conducting a systematic review as devised by Briner and Dreyer (2012) adapting from Higgins and Green (2008) was followed.

Table 5 Steps of the systematic review adapted from Briner and Denyer, 2012)

Step	Description
Background to review:	Definition of the problem and preliminary research; distinction from other research
Objectives:	Definition of the objectives and formulation of review questions
Criteria for considering studies for this review:	Outline of included research
Search strategy for identification of studies:	Determination of Data bases
Eligibility:	Elimination of studies that do not meet the pre-established criteria
Data collection:	Mode of data extraction and processing
Assessment of methodological quality:	Quality evaluation
Synthesis	Analysis of results

The scope of this review is to show the current state of knowledge regarding the circular economy in the AEC sector. By looking for successful projects in science and practice, conclusions can be drawn about the importance of the topic and its dissemination. Based on the hypothesis that science often precedes implementation in practice, a high dissemination in science and in practice suggests a high dynamic and an establishment of the topic in practice. Conversely, high relevance of the topic in research coupled with low dissemination in practice indicates the presence of challenges in implementation. The aim of the literature study is not only to present the state of the art in science and technology, but also to identify the barriers to implementation.

The leading review question is:

RQ1. What is the state-of-the-art research and practice of circular economy implementation in the construction industry?

It was found adequate to separate the question into two sub-questions regarding research and practice. Therefore, in section 3.2 successfully implemented projects in research will be addressed, while in section 3.3 the object is successfully implemented projects in practice. Furthermore, the individual selection criteria are refined according to the research question and presented in the respective section.

The target papers were selected following previous studies using theme-based specific and pertinent keywords in this research area, such as "circular economy," "construction," "construction industry," "building," "urban mining", etc. The keywords utilized were derived from a preliminary literature survey on this subject. (Çetin et al., 2021; Hossain et al., 2020b, p. 2) The complete list of search strings are listed in Table 51 in Annex II. The search was conducted in the online databanks Scopus, an *"abstract and citation database of peer-reviewed literature including scientific journals, books, and conference proceedings"* (Elsevier, 2023a), and Web-of-Science (WoS). The WoS primarily focuses on the citation impact of journals, while Scopus coverage is more comprehensive, including all WoS journals in the science fields, similar to the coverage of large literature databases. (López-Illescas et al., 2008, p. 314) To include both peer-reviewed and non-reviewed proceedings, Google Scholar was selected as a third database.

3.2. SUCCESSFUL IMPLEMENTED PROJECTS OF CIRCULAR ECONOMY IN THE BUILT ENVIRONMENT IN RESEARCH

The aim of the literature study is to find successfully implemented projects in research on CE in the BE. As projects are often interpreted as "case studies", which limits the research scope, the research problem was translated to:

RQ1. What is the state-of-the-art in research of circular economy implementation in the built environment?

Considering the state-of-the-art will surface current research achievements and therefore better fit the scope. Further research questions (RQ), which add to conciseness and should therefore be addressed, are:

RQ2. What are current research trends?
RQ3. What is the current knowledge regarding the implementation of CE in the BE?
RQ4. Which limitations and barriers are identified?
RQ5. What should future research focus on?

No limits were set for publication years in this SLR. Due to time and resource limitations for translations, only English publications were included. The initial query in Scopus, Google Scholar and Web of Science resulted in respectively 366, 916 and 281 articles and conference proceedings as of January 2023 (no limits for publication years).

The premise of a systematic literature search is to describe the state of research on a problem and to contribute to the body of knowledge by adding new findings. However, the preliminary search and consecutive statistical analysis (see 3.2.1) revealed that review-type publications constitute a large proportion of the body of knowledge and have a similar or identical research scope. This leads to the conclusion that the current state of research in this field is likely to be accurately represented, given the recent publication dates of the papers (the latest being January 2023, see section 3.2.1, Description of the research FieldAnnex III), the number of publications, and the similarities in research objectives. Hence, the document type was added to the selection criteria, delimiting the literature studies to open-access "reviews". This type of literature review which only includes review-type publications are denominated rapid overview of systematic reviews (or "umbrella overview"), a short form of SLR. While rapid reviews are undertaken in a shorter time-frame than SLRs, and limit the scope (e.g., use of grey literature) (Khangura et al., 2012, p. 6), they yield comparable results (Watt et al., 2008, p. 1039). Moreover, articles containing terms and expressions which were semantically different but homonyms (e.g., "construction" is used as "model construction") were eliminated, and articles focusing on a particular material (e.g., concrete or polymers), component, stakeholder (e.g., private economy) or branch (e.g. MEP) were eliminated. Furthermore, articles reviewing a single country's performance were not considered, as they do not give a general overview of developments in the circular economy in the built environment. This led to 28 relevant articles, which were then analyzed. The included publications are found in Table 54 in Annex II. The review is conducted according to the research protocol proposed in Table 6.

Table 6 Research protocol for the SLR "Successfully implemented projects of CE in the AEC in literature"

Steps	**Research**
Initial Review	Overview of current research of circular economy in the built environment: Statistical analysis: scientometric analysis of research panorama
Objective	Find recent review papers on the implementation of CE in BE
Criteria for considering studies	Review papers in English that studied CE implementation trends, BE, trends and barriers in academia
Strategy to obtain studies	Research in three databases (Scopus, Web of Science and Google Scholar) applying no timeframe; restricting the document types to reviews and the subject area to Engineering and Environmental studies
Eligibility	Peer reviewed and proceedings
Data collection	Exclusion of repeated articles and articles with no full-text available; articles focusing on particular material, component, stakeholder (e.g., private economy (or branch (e.g., MEP); exclusion of homonyms; read of title, read of abstracts; read of full articles; addition of relevant articles that were not included in this process
Quality assessment	Articles analyzed by the author according to
Synthesis of results	Scientometric analysis to identify trends, future research trends; Content analysis: Summary and results of all analyzed papers:

To generally describe and identify current research trends a statistical analysis based on this preliminary search was conducted. The statistical analysis is used to describe a broad research field based on the preliminary, i.e., unfiltered, search. It comprises a general description of the body of knowledge (publishers, geographic distribution, and publication years) and the science mapping. To efficiently conduct the statistical analysis the software SciVal and VOSViewer were used. SciVal is a visualization, benchmarking and analysis tool based on the Scopus database that provides access to the research performance of thousands of research institutions and their associated researchers (Elsevier, 2023b). VOSviewer, on the other hand, is a bibliometric visualization software that offers distance-based visualizations of bibliometric networks (van Eck and Waltman, 2014). This software delimits the use of only one database for each network and requires PubMed, Scopus, Web-of-Science, Dimensions or Led file-types for a bibliographic analysis. Since Google Scholar (916 results) does not export bibliometric data appropriately, Scopus was selected as reference database as the one with the second most results (366 results).

3.2.1. DESCRIPTION OF THE RESEARCH FIELD

The state of research can best be described using a descriptive overview of the research field and its development. For the general description the literature data was retrieved directly from SciVal. In total, the preliminary selection of 360 papers (no selection criteria applied) was analyzed following the perspectives proposed by Okorie et al., 2018):

(1) Circular economy papers across years;
(2) publications across journals and conference papers; and
(3) publications by geographical distribution.

Circular Economy Papers across Years

In the preliminary search, no limits were set for the publication year. However, according to the distribution over time, there were no identified relevant papers on Scopus before 2007 which focused on CE in the BE. Specifically, papers on this subject only emerged in 2007 with Man and Wenhu's article "Construction of circular economy industrial system" (Man and Wenhu, 2007) and have increased exponentially from 18 publications in 2017 to 111 in 2022. It can be inferred, that *„this topic of research is starting to gain traction in the built environment and will likely continue to grow in terms of number of publications"* (Benachio et al., 2020, p. 4). However, the total number of publications compared with other research focus in the AEC sector (e.g. BIM with 15.357 results, virtual reality 14.731 results etc.) confirm the observation, that research on the implementation of the circular economy in the built environment is still in its infancy (Adams et al., 2017; Akhimien et al., 2021; Benachio et al., 2020; Çimen, 2021; Ghisellini et al., 2016; Hossain et al., 2020a; Mhlanga et al., 2022; Munaro, 2019; Munaro et al., 2020; Osobajo et al., 2022; Yu, Junjan et al., 2022).

Publications across Journals and Conference Papers

The types of publications reviewed were selected by the identified subject areas, including: “Engineering”, “Environmental Science”, “Energy”, “Business, Management and Accounting”, “Social Science” and “Computer Science” (see Figure 20). The diverse range of subject areas covered in research indicates the multidisciplinary nature of the field. The most output is found in the fields of engineering, environmental sciences, and energy. Furthermore, across the types of publications and papers series, the results of the preliminary search appear in a great variety of journal and proceeding series (see Figure 22) (Andersen et al., 2022, p. 12). However, a few stand out as dominant publishers being Journal of Cleaner Production (n = 34), the IOP Conference Series: Earth and Environmental Science (n = 32), Sustainability Switzerland (n = 27), and Resources Conservation and Recycling (n = 20).

Papers by Geographical Distribution

Finally, an analysis of the geographic distribution found that publications were drawn from 60 countries (see Figure 24). The country with the greatest number of papers in this review was the United Kingdom (n = 49), tightly followed by China (n = 44), Italy (n = 34) and Spain (n = 28). Also, Europe was by far the continent with the most publications in this area, with 260 of the papers included in this review. The next continent was Asia with 112 publications.

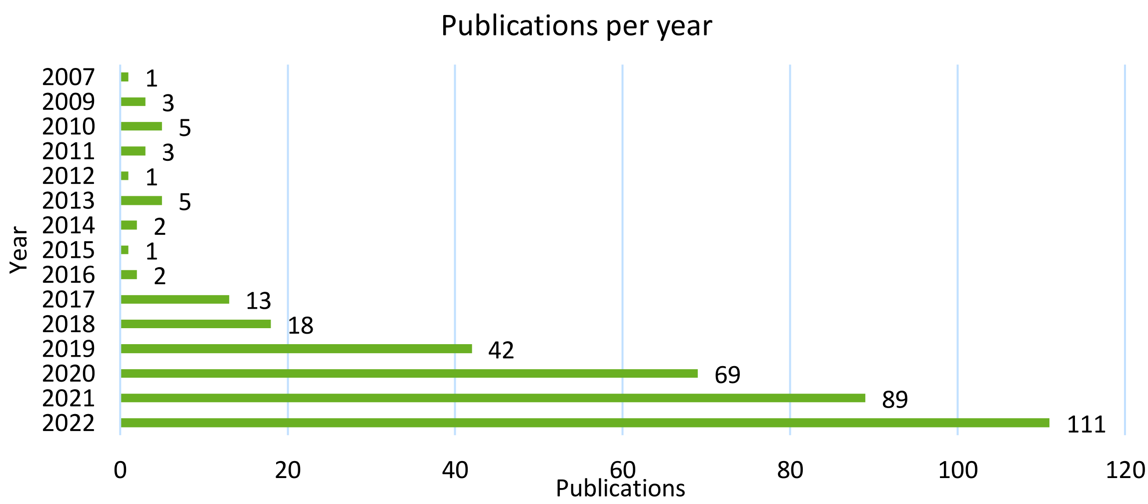

Figure 19 Number of Publications per Year of Publications for circular economy and BE (image by author)

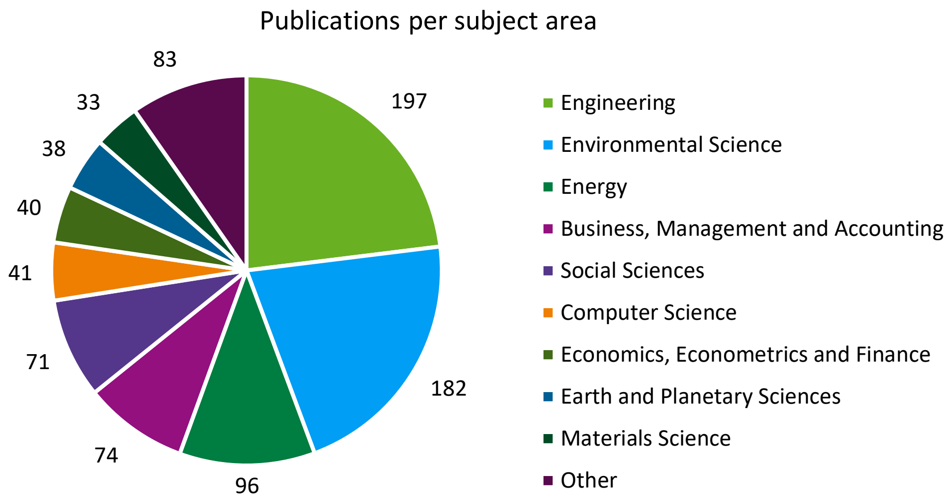

Figure 20 Publications by subject area (image by author)

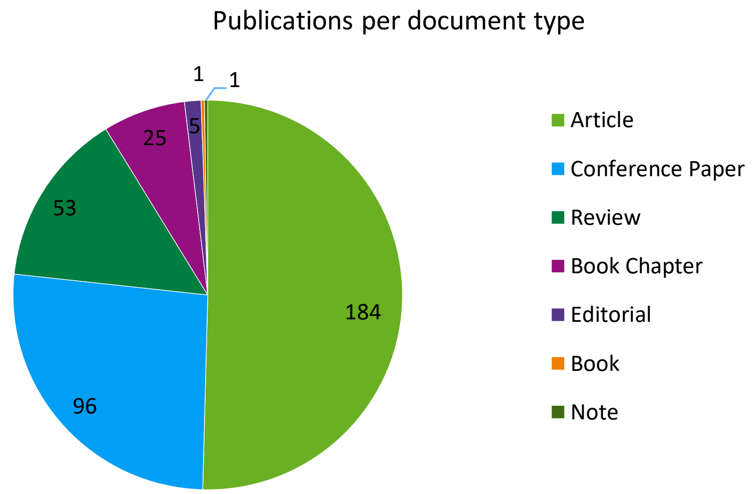

Figure 21 Publications per document type (image by author)

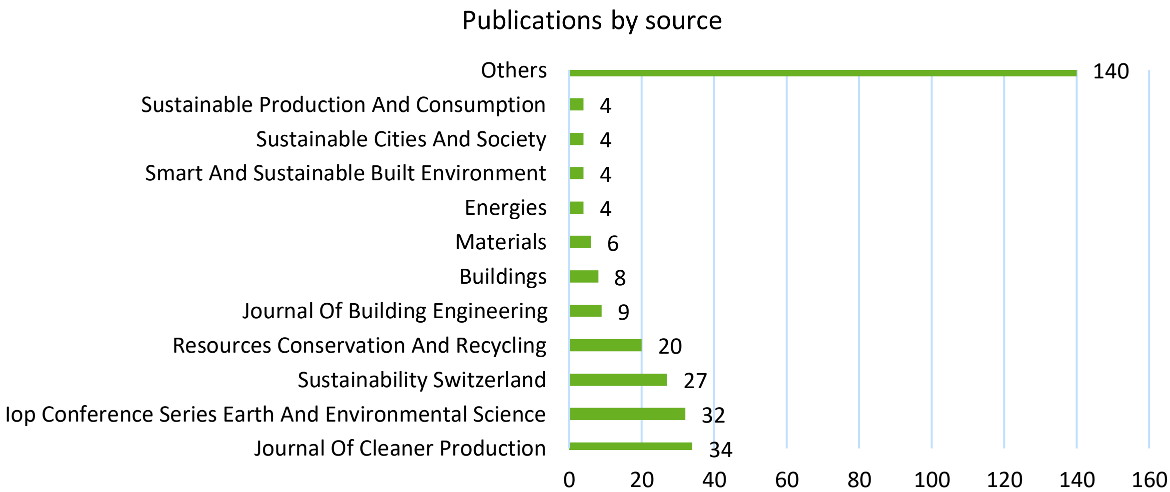

Figure 22 Publications by source (image by author)

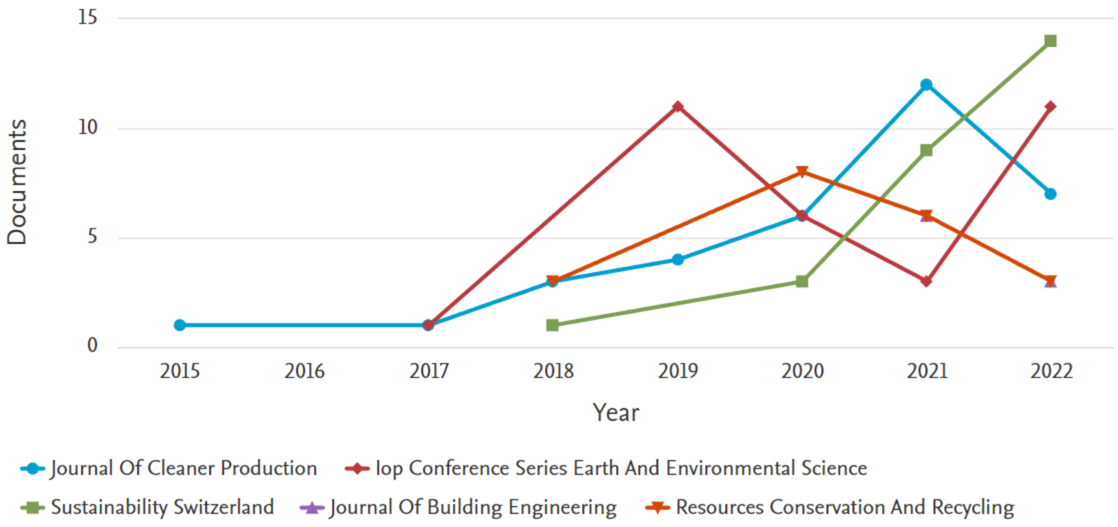

Figure 23 Publications by year by source (illustration from Scopus)

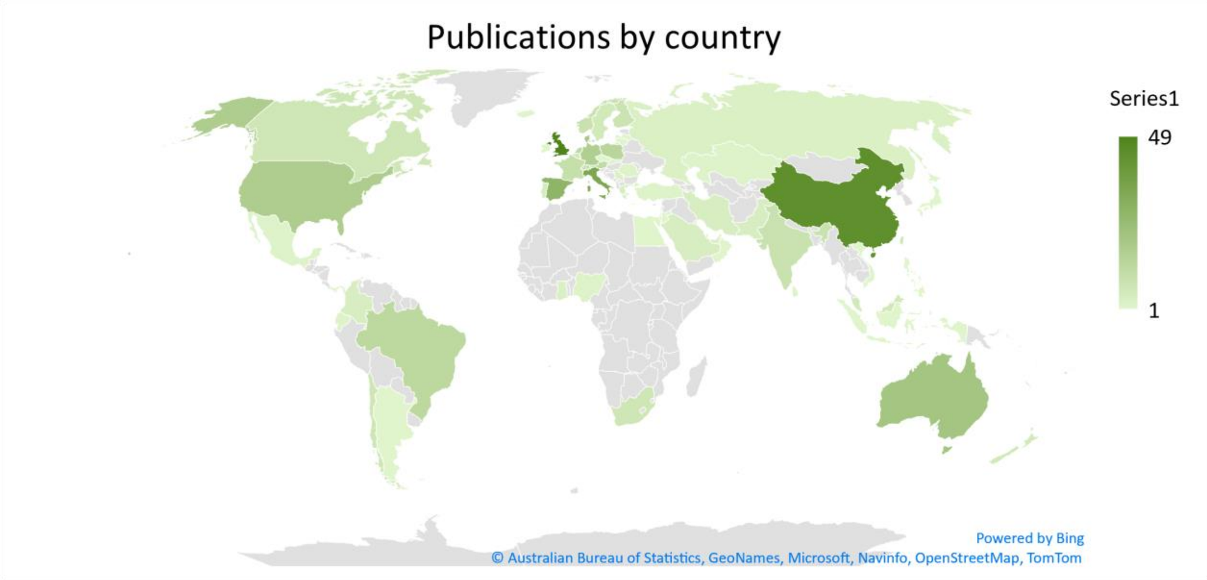

Figure 24 Publications by country (image by author)

3.2.2. RQ2. WHAT ARE CURRENT RESEARCH TRENDS?

The research trends, future research directions and thematic clusters within the thematic field of CE in the AEC sector were first identified using science-mapping techniques and then analyzed in a content analysis.

Science mapping

„Science mapping is a generic process of domain analysis and visualization“ (Chen, 2017), that „aims at detecting the intellectual structure of a scientific domain” (Darko et al., 2020, p. 2). The science-mapping included co-citation and co-word analysis, and bibliographic coupling and was conducted using the metadata exported as a tab delimited file (.csv) from Scopus. It is a valuable approach for identifying potentially significant patterns in extensive bibliographic data, and it can lead to insights that are not feasible with other methods (Darko et al., 2020, p. 2). Interrelated papers are grouped in clusters in which all papers share at least one reference with all the other members (Kessler, 1963, p. 10). Clustered papers have a high degree of logical correlation and therefore a similar content (Kessler, 1963, p. 10).

Bibliographic coupling

Bibliographic coupling is a grouping method for technical and scientific papers based on shared references. Two publications are coupled if they have at least one common reference or source (Kessler, 1963, p. 10). This technique is useful for the *identifying current trends*, as the publications' data (author name, title, journals, DOI and references) is used to "*analyze the relationships among citing publications to understand the periodical or present development of themes in a research field“ (Donthu et al., 2021, p. 289).* For the bibliographic coupling using VOSViewer the counting method was set as full-counting and the threshold of minimum numbers of citations was set at 10. This resulted in 131 papers, with the largest set of 125 clustered items. The resulting network is visualized in Figure 25.

The clusters show a high density with only a few publications (such as Rakhshan (2021a) or Deutz (2017)) outside. In general, the closer two nodes are located to each other, the stronger their relatedness (van Eck and Waltman, 2023, p. 9) Therefore, from the visualization it can be inferred that the publications reference sources with a similar thematic focus. This could also be an indicator that the body of knowledge is not very diverse yet, with a small number of landmark papers. In total seven thematic clusters were identified, that also have thematic overlaps among them. The clusters and their main topics are summarized in Table 7 (p.40). The central research trends can be summarized to: *principles and strategies/enablers, current challenges of CE in the BE; construction and demolition waste, reuse, design strategies; stock and flow analysis (including LCA and LCC); and tools and technologies.* This is consistent with the classification of various publications (Benachio et al., 2020; Ginga et al., 2020; Hossain et al., 2020b).

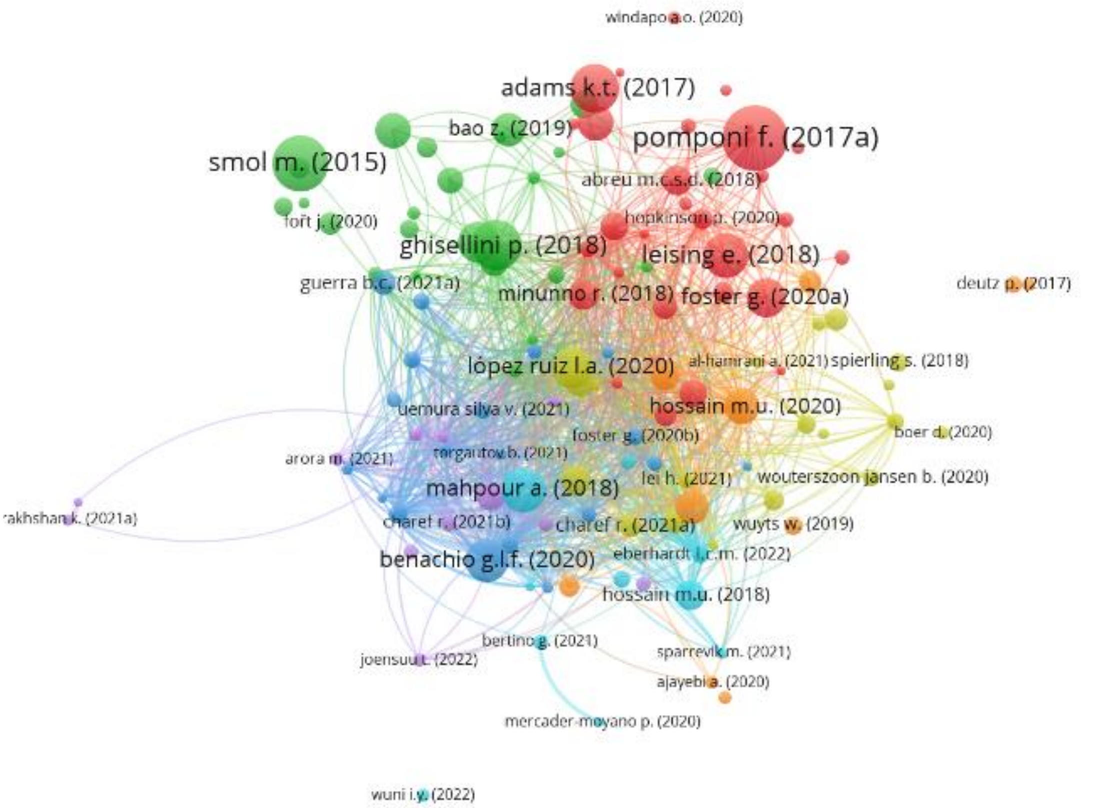

Figure 25 Literature clusters resulting from Bibliographic Coupling using VosViewer (image by author). In the visualization each publication that shares at least two sources with other publications is represented by a node. In bibliometric coupling the strength of a link between two nodes indicates the number of cited references two publications have in common (van Eck and Waltman, 2023, p. 5). The link thickness indicates the frequency of co-occurrence. Nodes and links of a particular color represent a thematic cluster and can explain the coverage of topics and relationships between topics within that cluster.

An important research trend is the Reuse of Materials and CDW management (Mhatre et al., 2021; Munaro et al., 2020; Osobajo et al., 2022, p. 52), in fact in Munaro et al. (2020) the category Recycled/Reusable materials comprised almost 40% of the studied volume. But, it is noticed that the amount of research done on recycling greatly outnumbers the research done on reuse. (Charef et al., 2021; Ghisellini et al., 2016; Ginga et al., 2020) To date, the applications of CE in construction practice had been largely limited to end-of-life considerations and recycling (Adams et al., 2017; Akhimien et al., 2021, p. 33; Mhatre et al., 2021), despite being the least preferred option on the R-frameworks (Charef et al., 2021). This could be explained by the CE's strong focus on technological innovation through cleaner technologies and recycling, rather than reuse.

Table 7 Thematic clusters resulting from bibliographic coupling

Cluster	**Most cited papers**	**Main topics**
Cluster1 (red)	(Adams et al., 2017) (Bilal et al., 2020) (Foster, 2020) (Hart et al., 2019) (Leising et al., 2018)	Current challenges, enablers/strategies and frameworks for CE implementation in the AEC sector
Cluster 2 (green)	(Akanbi et al., 2018) (Akanbi, L. et al., 2019) (Bao et al., 2019) (Esa et al., 2017) (Ghisellini et al., 2018) (Smol et al., 2015)	Construction and demolition waste reduction (management) and prevention (reuse); management tools;
Cluster 3 (dark blue)	(Akhimien et al., 2021) (Benachio et al., 2020) (Çimen, 2021) (Mhatre et al., 2021) (Oluleye et al., 2023)	Literature reviews on CE implementation in the construction industry; case-studies and stakeholder awareness;
Cluster 4 (yellow)	(Anastasiades et al., 2020) (Charef and Emmitt, 2021) (Gallego-Schmid et al., 2020) (Ginga et al., 2020) (Eberhardt et al., 2020) (López Ruiz et al., 2020)	Life cycle assessment (LCA) and environmental assessment; tools
Cluster 5 (orange)	(Hossain et al., 2020b) (Joensuu et al., 2020) (Munaro et al., 2020; Yu et al., 2021) (Yu et al., 2021)	Literature reviews, Circular economy practices/strategies; gaps and challenges;
Cluster 6 (cyan)	(Eberhardt et al., 2022) (Hossain and Ng, 2018) (Mahpour, 2018)	Design and construction strategies; Building LCA;
Cluster 7 (purple)	(Charef and Lu, 2021) (Minunno et al., 2020) (O'Grady, T. et al., 2021)	Stock and flow analysis, reusability evaluation; benefits/environmental impact analysis; disassembly

Co-word analysis or Keyword co-occurrence

While bibliographic coupling can provide an overview of the present research field, co-word analysis is used to preview the *future* of the research field (Donthu et al., 2021, pp. 289–290) and potential gaps. This mapping method gives an overview of the keywords used in the literature sample and elaborates on the content of thematic clusters.

For the co-word analysis all keywords with a minimum of five occurrences (at least five documents have that keyword) were considered. A thesaurus file was used in VOSviewer to merge different synonyms of keywords before creating a map based on bibliographic data, allowing for data cleaning and the correct weighting of the keyword or topic. (van

Eck and Waltman, 2023, p. 31). Keywords contained in the initial search query such as “circular economy” or “construction” and methodological keywords such as “literature review” were excluded. Of 2297 keywords, a total of 60 met the threshold (see Figure 26).

Table 8 displays the top ten keywords produced by the software, ranked in descending order of their links, and frequency of occurrence.

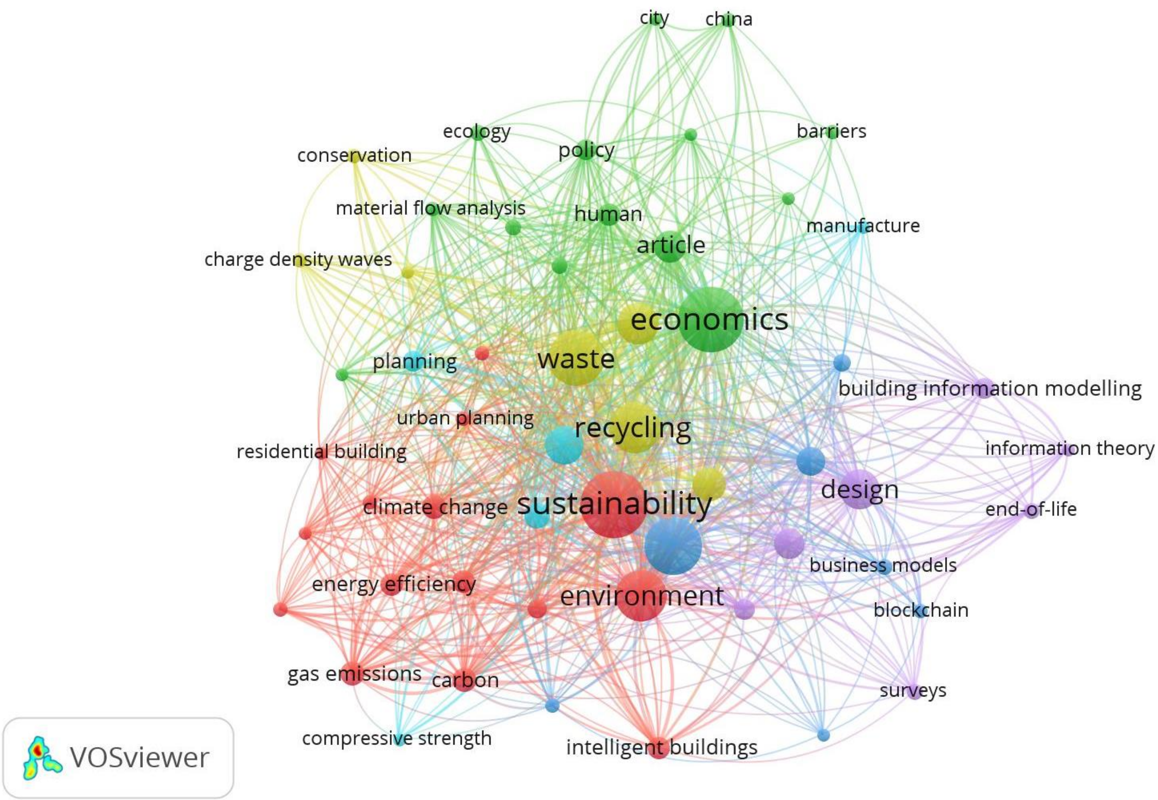

Figure 26 Cluster of keyword occurrence in review paper selection, VOSViewer (image by author). In this visualization each keyword is represented by a node where the node size indicates its occurrence, and the color denotes the distinct cluster. The node size indicates the number of documents a keyword appears in. (van Eck and Waltman, 2023) The link between two nodes determines the number of times a keyword was used together with another keyword. Additionally, the thickness of each arc signifies the strength of its respective relationship. (Wang et al., 2019, pp. 42–43)

Keyword co-occurrence clusters reveal thematic relationships and patterns within the text. Figure 26 identified six clusters of frequently occurring keywords that indicate common themes or concepts. For example, in design, the focus is on end-of-life considerations that translate into the Design for Disassembly (DfA) or Design for Deconstruction (DfD) strategies, and digital tools such as BIM are used to optimize these designs (Akhimien et al., 2021; Eberhardt et al., 2020). Another important topic is quantifying material flows and analyzing market-based potentials (Çimen, 2021; Munaro et al., 2020). Furthermore, the move away from recycling in favor of reuse plays a major role in construction demolition waste management (Ginga et al., 2020; Joensuu et al., 2020; Tirado et al., 2022). Overall, keyword co-occurrence clusters visually represent the text structure and facilitate the interpretation of the research topics.

Table 8 Most cited keywords analyzed by VOSViewer software.

Keyword	Cluster	Occurrences	Total link strength
sustainability	red	122	675
economics	green	117	676
life cycle assessment	blue	91	580
waste	yellow	89	552
recycling	yellow	74	516
environment	red	71	510
construction and demolition	yellow	49	353
design	purple	46	281
construction material	cyan	43	313
reuse	yellow	33	184

Co-citation

This analysis was done to provide an insight into understanding the intellectual structure of the research field and the various publication powerhouses which have been empowering research in CE in the CI (Antwi-Afari et al., 2021, pp. 5–6). In co-citation the link strength between two nodes indicates the number of times in which these two items were both cited by the same document (van Eck and Waltman, 2023, p. 27). For the analysis of co-citation in VOSViewer, the cited references were used as the unit of analysis, setting a minimum threshold of five citations per author. Of 18307 cited references a total of 56 references met the threshold, resulting in the diagram displayed in Figure 27.

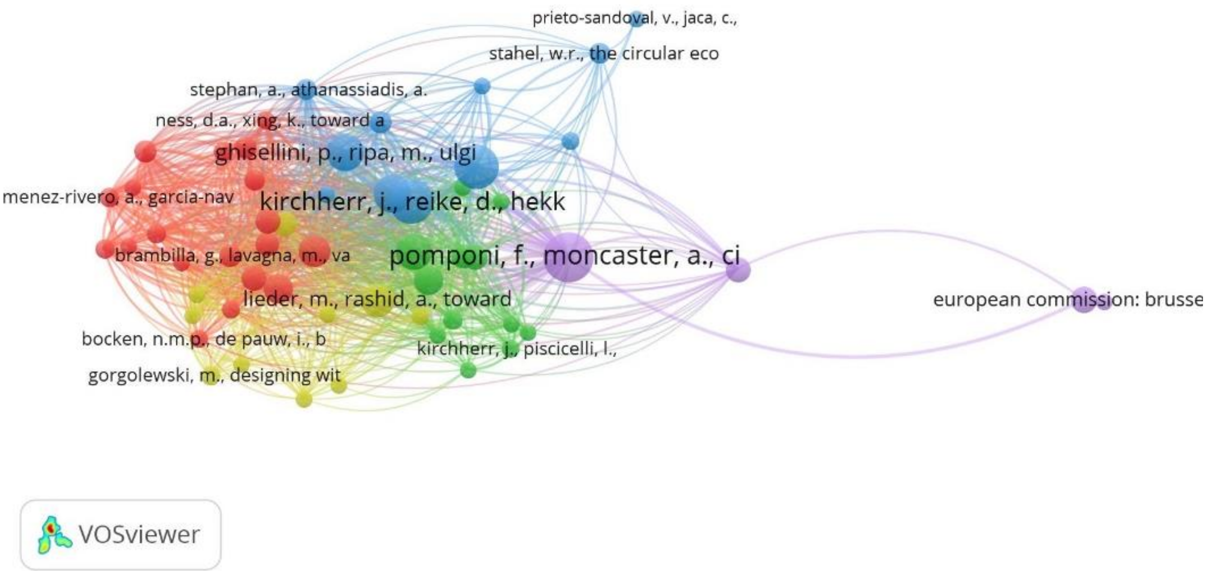

Figure 27 Visualization of the co-citation cluster, VOSViewer (image by author)

Figure 27 shows that all publications within a citation cluster are very close to each other. This indicates a high degree of interconnectivity and mutual influence among the cited papers. A high degree of agreement can be assumed with respect to the basic concepts, theories, methods, and results on the topic. This indicates that the research topic is well established and highly focused, with strong consensus and agreement among researchers in the field. However, it may be difficult to find breakthrough or novel ideas within the cluster in such a scenario, as most publications are likely to build on existing knowledge and reinforce established theories and methods.

3.2.3. RQ3. WHAT IS THE CURRENT KNOWLEDGE REGARDING THE IMPLEMENTATION OF CE IN BE?

Policymaking

A significant part of the studies on CBECE discuss the role of politics and policies in achieving a sustainable and circular economy (CE) within the construction industry. In research regulations and policies are being created and the main obstacles and motivators are outlined (Munaro et al., 2020, p. 13). According to Yu, Junjan et al. (2022) CE policies in construction currently have three functions: they aim to provide long-term financial support, use economic instruments to regulate secondary material market, and propose assessment standards for recovered material quality (Rios et al., 2022; Yu, Junjan et al., 2022, p. 9). However, among all policies and measures to promote CE transformation, both at the corporate and individual levels, financial subsidies are considered to be the most important (Çimen, 2021, p. 23; Munaro et al., 2020). But, CE policy-making will only be accomplished with the active participation of both public and private actors (Yu, Junjan et al., 2022, p. 10).

The EU has the highest concentration of CE policy initiatives compared to other regions. This is likely due to EU member states adopting CE guidelines from the European Commission and adapting their own strategies, while other countries need to develop CE innovations independently. (Yu, Junjan et al., 2022, p. 6) However, China has early developed its own CE policies that have an top-down approach and take into account the three implementation levels of micro, meso and macro (Bleischwitz et al., 2022, p. 2). Munaro et al. (2020, p. 15) suggest that the centralization of work in European countries and China demonstrates the result of the implementation of public policies and underlines that the expansion of research requires political and governmental support.

Tirado et al. (2022, p. 1) adds to it that local authorities play a crucial role in promoting circular economy (CE) strategies and economic dynamics in the built environment primarily because they possess the necessary skills and resources to implement large-scale CE initiatives. Their involvement in urban planning and their relationships with economic actors enable them to comprehend and master urban metabolism, which is a critical aspect of CE implementation (Tirado et al., 2022, p. 1).

Business Models

Circular business models adopted in the construction value chain are subject to research on the transition towards CE in BE (Çimen, 2021; Mhlanga et al., 2022; Munaro et al., 2020, p. 13). For example, research has been done on product life extension and take-back models, and industrial symbiosis. The on the lack of a market mechanism for the reuse of construction material, one of the barriers to waste valorization, was addressed in academia (Osei-Tutu et al., 2022, p. 16). Migliore (2019) proposed a virtual marketplace to facilitate inter-sectorial waste recycling. Gan et al. (2020) utilized a multidisciplinary approach to study the balance between human wellbeing and environmental sustainability through socio-technical solutions. (Çimen, 2021, p. 15)

Current research (Stahel, 2016) identified two groups of circular-economy business models, those that extend the service life of goods by reusing and those that create new resources through recycling (Charef, 2022, p. 2). In the former group, Adams et al. (2017, p. 22) identified viable take-back programs and high-value markets, assurance programs for reused materials, best-practice example case studies, and awareness-raising campaigns as biggest enablers. Furthermore, Çimen (2021, p. 23) proposed that financial organizations, such as banks and public entities, could be involved in a national resource bank to enable material leasing to developers, which could be encouraged over property ownership by communicating its benefits. Thus, the creation of circular business models requires a holistic approach including businesses, society, and government (Mhatre et al., 2021, p. 14). Frameworks have been developed that focus on supply chain collaboration, stakeholder networking, and capital planning for CE, providing a socio-technical framework for the implementation of CE in construction firms. Other studies stress the usage of interface management systems among stakeholders for adaptive reuse of buildings. However, none of the business models or frameworks have been validated, presenting a future opportunity for the development of a comprehensive circular business model (Mhatre et al., 2021, p. 18). According to Wuni (2022, p. 17), the most frequently cited critical success factors for circular construction projects are the following: the top management's awareness, commitment, support, and leadership; strong coordination, collaboration, and vertical integration among supply chain partners; sustained collaboration, communication, and information sharing among stakeholders and project team members; availability of supportive infrastructure and technological resources; and adequate financial resources and funding. Yu, Junjan et al. (2022, p. 12) noticed that Information and Communication technologies (ICT) solutions are gaining attention in the public sector as they improve business performance, streamline activities, and reduce principal-agent problems and transaction costs.

Reuse, Recycling and Construction and Demolition Waste (CDW)

Publications focusing on end-of-life interventions agreed in that material looping at the end of life (EoL) to a great extent increases resource efficiency and reduce waste (Akhimien et al., 2021, p. 33). The investigated EoL management methods in the CI include resource recovery practices such as sequential disassembly, deconstruction analytics, waste management best practices, and frameworks for construction and demolition waste management (CDWM) (Mhatre et al., 2021, p. 23).

Selective demolition should be performed for hazardous materials, with efficient handling to prevent contamination of recyclable materials. On-site sorting should be implemented to avoid waste mixing. The waste should be categorized based on its nature and potential economic benefits. Robust quality control systems should be put in place with proper checks and balances on material recovery methods, waste acceptance criteria, material properties, and the advantages and disadvantages of using materials in construction activities. (Purchase et al., 2021, p. 21) Furthermore, the site's culture and environment should be taken into account. Cutting waste can also benefit from a thorough waste audit and the establishment of a waste index (Purchase et al., 2021, p. 7). Ultimately, it is possible to transform a *conventional* project-product-delivery-cycle into a *closed-loop* project-product-delivery-cycle in line with CE, which would focus on reusing or recycling the material after the service life ends (Çimen, 2021, p. 23).

The recycling of waste materials in construction has been shown to have positive impacts on the environmental, economic, and durability aspects of construction activities (Akhimien et al., 2021; Purchase et al., 2021, p. 21). While recycling is inherently energy-consuming, it is often more advantageous to recycle construction and demolition (C&D) materials rather than dispose of them in landfills, due to the social and environmental benefits (Purchase et al., 2021, p. 20). Ginga et al. (2020, p. 16) not only concluded that it is possible to use ≥40% recycled construction and demolition waste in new construction applications based on the current physical and mechanical property studies, the study also found that a 100% replacement of recycled materials is viable in nonstructural applications. The research, tests, and results on recycling materials indicate that construction materials with recycled components possess physical and mechanical properties that are nearly the same as those of their original counterparts. Construction materials with slightly lower mechanical properties can be compensated for by adding additional materials. This slight decrease is minimal compared to the environmental and sustainability benefits of recycling CDW. (Ginga et al., 2020, p. 16)

However, the main focus on recycling is using C&D waste in concrete manufacturing and reducing the use of natural aggregates (Munaro et al., 2020, p. 13). Studies gathered specific construction suggestions that can improve the recyclability of building materials including the usage of bolt and nut joints instead of nails and gluing, along with using prefabricated assemblies and layering building components according to their anticipated lifespan. Minimizing the variety of building components and standardizing them is also necessary for increased recyclability and exchange within the circular economy. (Akhimien et al., 2021, p. 28)

Moreover, research focused on the reuse of waste considered waste from various sources and on their reuse in the construction value chain. This includes using the waste as an additive or replacement in materials, and creating new products that have the same or improved performance. The research also examines the quality of secondary materials, and best practices for reducing environmental impacts. (Munaro et al., 2020, p. 13)

Sáez-de-Guinoa et al. (2022, p. 13), argued that despite a known feasibility and the resulting benefits, for some building components and materials, the reuse is limited by a lack of specialized recycling facilities, the low value of (new) material and common practice, which prefers landfilling or incineration.

Finally, studies propose frameworks and strategies for CE implementation for CDW reduction. Ginga et al. (2020, p. 1) propose a CE framework, with an emphasis on the recovery and production of materials, particularly the reuse and recycling of CDW into new construction applications. Hossain et al., (2020b, p. 2), summarized these implications in literature to: "*(1) improving the use of sustainable materials which is achievable by integrating the collaborative benefits among all parties involved in the construction project, (2) promoting material efficiency by recycling/reusing the construction wastes, and (3) avoiding the production of unnecessary wastes and consequently disseizing them to landfill" (Hossain et al., 2020b, p. 2)* and "*(4) development of recovery schemes "(Purchase et al., 2021, p. 3).* Additionally, Purchase et al. (2021, p. 3) also suggested the use of technologies such as BIM to overcome challenges in managing waste in large-scale BE.

Although these notable studies have developed frameworks, models, and methodologies to measure the recycling potential of CDW materials accurately, they fail to provide a unique definition for the potential of the circular economy (Akhimien et al., 2021; Papastamoulis et al., 2021). In contrast, Akhimien et al. (2021, p. 33) found that both designing out of waste (or design for waste prevention) and the use of buildings as material banks were considered as best solutions for reducing waste generation.

Design

Substantial research has been done on the identification of design strategies that enable circularity in construction projects. Despite their increasing development and implementation, the building industry currently lacks a coherent and widely accepted direction, resulting in an unorganized process (Eberhardt et al., 2022, p. 2). That is why in research a wide range of design strategies and categorizations is found: Charef et al. (2021, p. 2) created a classification of the current design into five categories approaches in response to the lack of consensus: prefabrication, design for change, design for deconstruction, reverse logistics, and closed-loop systems. On the other hand, Sáez-de-Guinoa et al. (2022, pp. 7–9) analyzed the strategies present in the market and identified two mayor design considerations (Designing out Waste and Resource Efficiency and Design for Energy), that enable a transition a CE when implemented during the design phase. Akhimien et al. (2021, p. 19) identified the design strategies Design for Disassembly (DfD) and Design for Recycling. In the DfA field, most studies investigated the adaptability of materials to recycling, while others focused on the reduction of material consumption through reusable components.

However, the two most cited design strategies for the implementation of CE in the BE were Design for Disassembly (DfD) (Akhimien et al., 2021; Anastasiades et al., 2020; Charef, 2022; Hossain and Ng, 2018) and Design for Adaptabiliy (DfA) (Anastasiades et al., 2020; Charef, 2022; Eberhardt et al., 2022; Hossain and Ng, 2018).

Akhimien et al. (2021, pp. 23–25) found publications on DfD comprising the concept development, the technical requirements and its connection to prefabrication. There are quantitative studies on the benefits and challenges of using prefabrication in construction, and an extensive review has proposed a map to show the trend of prefabrication in the CE (Charef, 2022, p. 1). In contrast, Eberhardt et al. (2022, p. 101) found that assembly/disassembly is the most commonly cited strategy in the literature, suggesting that the approach had become established in the building industry over the past decade.

Studies agree in that CE should be adopted during the early stages of design to select the best strategies and tools, as this phase is decisive in the overall performance of buildings (Benachio et al., 2020; Mhlanga et al., 2022; Munaro et al., 2020, p. 15). By considering CE practices earlier in the project design stage, it is also possible to incorporate them into the life-cycle assessment of the project, which can show the benefits of reusing materials and reducing resources taken from nature in terms of reducing emissions, embodied carbon, and energy (Benachio et al., 2020, p. 10). Furthermore, the nature of waste products is determined in the design stage (Mhlanga et al., 2022, p. 19). Following the 3Rs (reduce, reuse, and recycle) hierarchy of the circular economy, building components that are not reusable or adaptable should be designed with preference to their recyclability potential (Akhimien et al., 2021, p. 26)

Urban mining: Stock and flow analysis

A major challenge is the "understanding the spatial and temporal composition and organization of stocks and flows" (Tirado et al., 2022, p. 6). Research focuses on the development of material or urban stock models to predict the potential for resource recovery or urban mining. To achieve this, tools such as material passports and material flow analysis have been widely employed (Mhatre et al., 2021). Tracking material stock and flow along with the information to be stored in an internationally standardized resource bank is an important challenge, as with the emerging understanding in CE, raw material and waste are now considered equally important resources for both new construction and renovation (Çimen, 2021, pp. 23–24).

Articles on material stock focused on the creation of models to estimate the existing or future quantity of materials that can be reused on buildings in their end of life (Benachio et al., 2020, p. 9) and to quantify associated environmental impacts, including solid waste pollution and air emissions (Yu, Junjan et al., 2022, pp. 10–11). *"Deploying the circular economy at the stock level is essential because it will provide a better understanding of the flows of materials, energy, water, and goods"* (Tirado et al., 2022, p. 13). Several articles found that it is possible to create material stocks in a large scale, such as a whole city, by the means of existing data (Benachio et al., 2020, p. 9).

Two papers are particularly noteworthy (Benachio et al., 2020, p. 12): Oezdemir et al. (2017) developed a framework to assessing the material stock available in residential buildings in an urban region of Germany, by extracting the data from GIS and reviewing this data with previous studies about the material values, creating a cadaster of secondary resource that will be available to reuse in the future. Furthermore, Heinrich and Lang (2019) used geometric data from a city 3D model to calculate the material stocks in the district of Munich, as well as material data from the literature to determinate the potential date for several material self-sufficiency. Similarly, Kleemann et al. (2017) analyzed the building structure (buildings differentiated by construction period and utilization) of Vienna combining the geographical information systems (GIS) data from different municipal authorities (2017, p. 368).

The integration of BIM and GIS for inventory at the regional level is also considered in some publications: In their study, Wang et al. (2019) conducted a comprehensive review on the integration of Building Information Modelling (BIM) and Geographical Information Systems (GIS) in sustainable built environments (2019, p. 41), while Rua et al. (2013) present an urban application utilizing the ESRI City Engine Software (CE), which integrates Geographic Information Systems (GIS) and Building Information Modelling (BIM) concepts, and demonstrates its potential through spatial analyses (2013, p. 265).

Circularity Assessment

Research has been done on the assessment of CE based on circularity indicators (Yu, Junjan et al., 2022, p. 8).

The implementation of CE lacks a suitable and usable measuring methodology (Andersen et al., 2022). Even established certification systems such as BREEAM and LEED that promote sustainability in construction through life cycle assessment, do not yet evaluate circularity yet (Anastasiades et al., 2020), which leads to the creation of new approaches, frequently derived from the European standard for construction or another Life Cycle Assessment methodology (Andersen et al., 2022).

Furthermore, it is objected that the LCA used for assessing CE in BE has a similar focus as research in the linear economy. While there are some studies that challenge the methods used, most studies focus on determining the benefits of a proposed CE action through a static analysis, either by considering the upfront reuse or recycling, or by calculating the potential reduction in materials usage during the next service life. (Andersen et al., 2022). Moreover, the conclusion on the benefits of CE is typically based on a single indicator, such as climate change, and neglects other important environmental parameters and challenges (Andersen et al., 2022). Therefore, Bleischwitz et al. (2022, p. 10) recommend developing new core indicators for the circular economy and decarbonization, considering any synergies and trade-offs with socio-economic developments. This could be done by utilizing existing data on material and carbon footprints and implementing a common accounting framework for publicly listed companies. Collaborative research is encouraged to develop joint core indicators and learn from existing data sets. The goal is to improve research with societal impacts and support international collaborations of decarbonization and the CE. (Bleischwitz et al., 2022, p. 10)

Bilal et al. (2020) developed a circular economy assessment scale for the building sector in developing countries, consisting in 7 CE dimensions (Energy indicators, General circular economy indicators, Water indicators, Material indicators, Emission indicators, 3Rs (Reduce, Recycle and Reuse) indicators and Waste indicators) and 24 CE indicators (Bilal et al., 2020, pp. 1–12). Furthermore, several CE indicators to quantify the circularity of products and companies, which are focused on the micro-scale, and to measure circularity at the city level, the macro-scale, have been developed (the latter mostly in China). It's important to note that the micro-scale indicators cannot be used to measure circularity at the macro-scale, and vice versa (Anastasiades et al., 2020, pp. 13–14). However, there is a lack in research of circularity indicators that evaluate the meso-scale, specifically the construction and the building (Anastasiades et al., 2020, p. 14). Rosen (2020) tackled this issue by introducing and developing the Urban Mining Index (UMI), a methodology to evaluate and quantify the circularity potential of building structures in new construction design. This approach considers factors like material quality, economic feasibility, and the practicality of selective dismantling (Rosen, 2020, p. 10).

Tools to support CE: BIM, Building Material Passports (BMP)

According to Munaro and Tavares (2020), research in the area of tools and assessment to support circular buildings includes deconstruction process simulation, circularity index systems, BIM compliance, tools to support buildings as a material bank, and life cycle assessment (LCA) and life cycle costing (LCC) for comparing the environmental performance of different constructive systems. However, only a small percentage of publications include digital tools (Hossain et al., 2020b, p. 3). In their review, Hossain et al. (2020b) found that only a small percentage of the studies used LCA software (9%), BIM (9%), or fuzzy analysis (3%) while GIS was among the most commonly used tools. (Hossain et al., 2020b, p. 3) However, the most comprehensive review of CE enabling technologies was conducted by Cetin et al. (2020), who identified a total of ten digital technologies: additive/robotic manufacturing (AM/RM), artificial intelligence (AI), big data and analytics (BDA), blockchain technology (BCT), building information modelling (BIM), digital platforms/marketplaces (DP), digital twins (DT), the geographical information system (GIS), material passports/databanks (MP), and the internet of things (IoT). (Çetin et al., 2021, p. 1)

In the construction industry, the prevalent Information and Communication Technologies (ICT)-based decision-making tools include BIM and GIS, Radio Frequency Identification (RFID) and Modelling Simulation (MS).

Table 9 Identified CE enabling digital technologies (DT)

Identified Digital Technology		**References**
Additive and Robotic Manufacturing	AM/RM	(Çetin et al., 2021)
Artificial Intelligence	AI	(Çetin et al., 2021), (Platten et al., 2020),
Big Data, and Analytics	BDA	(Çetin et al., 2021), (Yu, Yazan et al., 2022)
Blockchain Technology	BCT	(Çetin et al., 2021), (Yu, Yazan et al., 2022),
Building Information Modelling (BIM)	BIM	(Akanbi et al., 2018), (Çetin et al., 2021), (Yu, Yazan et al., 2022)
Digital Platforms	DP	(Çetin et al., 2021),
Digital Twins	DT	(Çetin et al., 2021)
Disassembly and Deconstruction Analytics System	D-DAS	(Akanbi, L. A. et al., 2019)
Geographical Information System	GIS	(Çetin et al., 2021), (Rua et al., 2013), (Wang et al., 2019), (Yu, Yazan et al., 2022),
Internet of Things	IoT	(Çetin et al., 2021), (Yu, Yazan et al., 2022)
Life Cycle Assessment	LCA	(Xue et al., 2021)
Material Passports and Databanks	MP	(Sauter, 2018), (Benachio et al., 2020), (Munaro, 2019), (Çetin et al., 2021), (Honic et al., 2019), (Ogunmakinde et al., 2021)
Radio Frequency Identification	RFID	(Yu, Yazan et al., 2022)

In construction, AM/RM is used for concrete printing, building component fabrication, assembly of timber or metal elements, digital casting, and precise milling or drilling. Its applications include resource optimization, waste reduction, material recycling, tailored connections for reuse, modular design, safer working environments, and advancements in bio-based 3D printing (Çetin et al., 2021, p. 14). BDA refers to the analysis of large and diverse data sets using techniques like statistics and machine learning. In the construction sector, BDA offers opportunities for resource optimization, generative design, performance prediction, personalized services, energy management, and smart buildings and cities when combined with IoT (Çetin et al., 2021, pp. 15–16). Furthermore, it offers opportunities for data-driven solutions to minimize waste, enables the investigation of numerous projects over time, facilitates seamless integration with Building Information Modeling (BIM), and supports CDW management (Yu, Yazan et al., 2022, pp. 5–6).

Blockchain technology offers secure and transparent information management in the construction industry, with potential applications in notarization, transaction management, and provenance tracking. Integrating blockchain with BIM improves information traceability, scheduling control, and waste management optimization (Yu, Yazan et al., 2022, p. 6). Furthermore, it is applied for timestamping BIM model changes, recording asset ownership, maintaining material passports, automating building maintenance, enabling complex information networks in supply chain management, facilitating material passports, and enabling secure peer-to-peer trading networks (Çetin et al., 2021, pp. 16–

17). The use of BIM to facilitate the transition towards CE has been explored in several studies: studies have been published that demonstrate BIMs potential for reducing construction and demolition waste, its use to support the implementation of CE in BE, and its use for the optimization of deconstruction activities, (Charef, 2022, p. 2) In the context of waste minimization and management, Yu, Yazan (2022) identified three key functions of BIM: First, it is crucial to quantitatively predict waste in advance for the analytics of construction and demolition waste (CDW) management because there is limited time allowed for material recovery at the end-of-life (EoL) phase (Akanbi et al., 2018; Yu, Yazan et al., 2022, p. 4). Second, BIM can contribute to waste minimization through design. Moreover, BIM plays a role in evaluating environmental and economic performance (Yu, Yazan et al., 2022, p. 5). Akanbi et al. (2019) propose a "Disassembly and Deconstruction Analytics System" (D-DAS) to assess the end-of-life performance of buildings from the design stage. It extends the capabilities of BIM software to evaluate building designs in line with the circular economy principle and Design for Disassembly and Deconstruction. The system consists of four layers and provides three key functionalities: Building Whole Life Performance Analytics, Building Element Deconstruction Analytics, and Design for Deconstruction Advisor. It serves as a decision support platform for assessing compliance with circular economy and sustainability requirements. (Akanbi, L. A. et al., 2019, p. 386) Finally, BIM enables high-quality collaboration to achieve efficient CDW management (Yu, Yazan et al., 2022, p. 4).

In conclusion, BIM has a key role in the technological advancements for implementing the CE in the CI as it optimizes design to reduce resource consumption and waste generation through (1) storing, sharing, and monitoring life-cycle information of materials, (2) providing a collaborative virtual environment for different stakeholders to communicate, visualize, and validate project details across the entire life-cycle, and (3) serving as an information repository that can be integrated with various techniques, thus enabling flexible CE-oriented functionalities. (Yu, Yazan et al., 2022, p. 5)

Finally, research focuses on the creation of Building Material Passports (BMP) "*that can be used to store important data of these building components for their use in their end of life, helping incorporate the materials in the circular loop, instead of disposing them" (Benachio et al., 2020, p. 9).* Material passport are considered a valuable tool for facilitating the knowledge transfer about building components and materials (Anastasiades et al., 2020), and are frequently employed in connection with the development of material or urban stock models to predict the potential for resource recovery or urban mining (Mhatre et al., 2021). In this context, the BAMB (Buildings as Material Banks) project, an EU-funded initiative, investigated and sought circular solutions to preserve the value and functionality of building materials and systems. The research developed a software platform that generates three types of Material Passports: *"one for products, one for buildings and one for instances*" (Buildings As Material Banks, 2019, p. 14)

3.2.4. RQ4. WHICH BARRIERS TO THE SUCCESSFUL IMPLEMENTATION OF CE IN BE ARE IDENTIFIED?

The barriers in the successful implementation of CE practices have been object to extensive research and can be grouped into five main categories (Purchase et al., 2021, p. 1): legal, technical, social, behavioral, and economic.

Despite the known importance of the construction industry in the implementation of the CE, existing policies are insufficient to address complex CE challenges (Yu, Junjan et al., 2022, p. 6). Policymakers face difficulties in finding efficient and tangible methods to support the construction industry due to the industry's distinctive features, while industrial actors await policy support in order to advance the implementation of the CE. (Yu, Junjan et al., 2022, p. 2) One of the legal barriers is the scope of the policies. Currently, governments establish ambitious recovery rates for construction and demolition waste (CDW) as part of their national policy visions, and high-level managers develop various action plans for achieving a circular economy (CE). However, the policies fail to address the root causes of waste generation or are formulated too broadly (Ghisellini et al., 2016, p. 27). As an example, EU policies concentrate on end-of-pipe solutions, i.e. solutions that focus on dealing with waste and pollution after it has been produced, rather than addressing the root causes of these issues (Charef et al., 2021). Another legal barrier is the insufficient guidance for implementation in practice. Existing policies lack effective frameworks to manage and supervise construction projects compliant with established CE principles (Charef et al., 2021; Yu, Junjan et al., 2022, p. 6). Limited information is given on how local industrial actors should implement these visions on a practical level (Yu, Junjan et al., 2022, p. 10). These policies lack clarity on how to effectively obtain and sort construction and demolition waste and do not set standards in the recycling and reuse of such waste. (Akhimien et al., 2021), which further exacerbated by limited design codes that focus on the use of reclaimed materials (Osei-Tutu et al., 2022, p. 20).

Technical barriers include procedural and technological challenges resulting from the implementation of CE principles in the construction project. From the contractors' perspective, the main procedural challenges for small-scale companies include the dismantling, segregation, and on-site sorting of C&D waste, transportation, and local recovery processes. (Akhimien et al., 2021; Purchase et al., 2021, p. 1) The materials resulting from the mining process need to be allocated for treatment or storage across different geographic locations (e.g., construction sites, material banks, resource centres, and landfills) throughout their lifespan (Papastamoulis et al., 2021) and inadequate monitoring of waste management remains a significant issue in the industry. (Osobajo et al., 2022, p. 46). The lack of knowledge and metrics about the potential for product reuse at the end of life is a significant issue in the construction industry. Reuse of secondary materials faces challenges related to insurance, guarantee, quality, and performance, particularly structural capacity .(Munaro et al., 2020, p. 14)

Among the technological critical issues, the following are the most important: availability of supportive infrastructure and technological resources, integration of digital technologies, adequate expertise and knowledge of the project team members in circular construction projects, staff education and training, and process integration technology for cleaner production (Osei-Tutu et al., 2022; Wuni, 2022, p. 5). To keep up with the rapidly growing number of available circular economy (CE) solutions for the built environment, an interconnected database of best practices and appropriate evaluation methods is required (Joensuu et al., 2020, p. 16).

Market dynamics and the economy are primary deciding factors for the acceptance of reused (structural and non-structural) elements in the construction industry (Çimen, 2021, p. 24). Thus, one of the most important economic barriers is that the required market mechanisms to support material circularity and manage the construction industry's complexity and interaction with other sectors, have yet to be developed (Çimen, 2021, p. 23). Business models and supply chain integration provide the basis for CE practices in the construction industry (Adams et al., 2017; Charef et al., 2022; Mhlanga et al., 2022, p. 6) A compelling business case with commercial feasibility is critical for enabling a shift in current practices (Adams et al., 2017, p. 22), so that the insufficient market value for reclaimed materials is a crucial economic barrier. Other obstacles impeding competitivity are: *"strict quality assurance systems, market uncertainty about availability of waste materials, knowledge and negative perceptions, high cost of material recovery related technologies, etc."* (Purchase et al., 2021, p. 21).

In the social and behavioral category, the risk perception among users is a major factor in the utilization of reused materials in new construction (Çimen, 2021, p. 24). Reused and recycled products are perceived as environmentally friendly but of lower quality (Ginga et al., 2020; Osei-Tutu et al., 2022) The prevalent mindset of actors in the construction and demolition industry is to regard C&D materials as waste rather than a potential resource and fail to fully tap into their value (Purchase et al., 2021, p. 16). To overcome this barrier, the promotion of circular economy in the built environment can be initiated through public projects, but there must also be bottom-up motivation from all industry decision-makers in order to successfully implement circular economy principles. (Çimen, 2021, p. 24)

3.2.5. RQ5. WHAT SHOULD FUTURE RESEARCH FOCUS ON?

Yu, Junjan et al. (2022) identified an important research gap in the understanding of how policies can support CE transition in the built environment. Current studies on policy initiatives are based on conventional supply chains for the building industry without fully incorporating CE. Furthermore, while most research examines the overall factors that facilitate or hinder the implementation of circular economy (CE) and emphasizes the importance of policy support in enabling the transition to a CE, there is a lack of guidance in the literature on how the suggested policy alternatives can be effectively implemented throughout the policy cycle.(Yu, Junjan et al., 2022, p. 10) Also, further investigation of policies that promote CE in CBE through financial incentives and regulations is the interaction of cross-sectoral waste policies is needed (Çimen, 2021, p. 23).

Furthermore, research gaps in the development of new business areas that do not support the linear model and the adaptation of current business models in the construction industry to new services emerging from CE are highlighted (Benachio et al., 2020, p. 10). For example, empirical evidence on the effects of sharing economy practices (Joensuu et al., 2020, p. 16) and research focusing on how new business models can enable materials to increase their residual values (Munaro et al., 2020, p. 1) are needed. On one hand, research should be conducted on extended producer responsibility (EPR) in the building industry to establish a virtual building material bank that could serve as a new marketplace for reusable building components. (Joensuu et al., 2020, p. 16) On the other hand, research to identify influences of supply chain integration and risk management frameworks is needed to enable existing supply chain organizations to re-evaluate their processes (Osobajo et al., 2022, p. 52).

Future research in the construction industry should explore the utility of whole life cycle costing (LCC) in designing circular economy models for construction operations. LCC considers social, environmental, and governance aspects and has the potential to reduce construction costs. (Osobajo et al., 2022, p. 51) Cost modeling through material reuse and feedback loops using Kaizen costing may be a potential research area in construction management (Osobajo et al., 2022, p. 51)

Regarding circular design and construction strategies, research has not adequately addressed key areas, such as circular product design, end-of-life considerations (including quality and economics), and modular integrated construction. (Antwi-Afari et al., 2021, p. 1) The choice of design and construction strategies in the literature is often based on intuition, due to a lack of knowledge about the environmental performance and benefits of these strategies (Eberhardt et al., 2022). This knowledge gap potentially hinders more focused efforts and greater uptake of circular economy practices in the building industry (Adams et al., 2017, p. 15; Munaro et al., 2020) Furthermore, research is needed to identify overlooked strategies from pre-existing concepts, to explore parallel developments in science, policy, and practice and to establish a common understanding of identified strategies and their technical aspects (Eberhardt et al., 2022, p. 108), making research into standardization necessary (Anastasiades et al., 2020) Moreover, the interactions between different design and construction strategies, effective strategy combinations and conditions for their success should be explored (Eberhardt et al., 2022, p. 108). To address this issue, the development of a new design typology or framework that structures and prioritizes the circular economy strategies based on their potential to minimize building-related environmental impacts is needed (Eberhardt et al., 2022, p. 108). Lastly, there is a limited number of published studies that focus on creating or discussing CE indicators (Ghisellini et al., 2016, p. 14), which are needed to determine the circularity of a project.

The application of reuse into new construction functions is yet to be explored and the lack of quantitative information on quality requirements restricts its potential usage in practice (Ginga et al., 2020, p. 15). Further experimentation is needed on the optimal proportioning of recycled, natural, and other materials to maximize recycled CDW use (Ginga et al., 2020, p. 16) and increased research efforts should be made into standardization of material sizes and types (Akhimien et al., 2021). Although attempts have been made in many cases, there is still limited investigation on practicality of incorporating CE in the modern built environment at a large-scale. Unlike small- and medium-scale construction projects, there are more challenges associated with adapting CE to large-scale applications. (Purchase et al., 2021, p. 3)

Lastly, research into easily adoptable tools to achieve CE in construction is required. (Charef, 2022, p. 2). There is a lack in information and technology (ICT)-based tools to support decision-making that consider the entire life-cycle as existing tools (BIM, GIS, RFID, MS, etc.) mostly focus on one life-cycle stage, mainly the EoL-phase (Yu, Yazan et al., 2022, p. 14). Future research should therefore focus on improving data management support to enhance regional data sources for CDW and enable accurate data-driven decision-making. Technology integration should also be improved by using BIM as a central information hub to integrate data collection and analytic technologies. An integrated decision support system is needed to articulate the interrelationships among technologies, stakeholders, and applications. In addition, there is a need to propose an approach to form a closed-loop supply chain by integrating 3R principles into circular business models. Coordination strategies for secondary material markets and ICT-based solutions to enhance public-private collaborations and improve the efficiency of CE policy-making should also be developed. (Yu, Yazan et al., 2022, pp. 14–15)

3.3. SUCCESSFUL IMPLEMENTED PROJECTS OF CIRCULAR ECONOMY IN THE BUILT ENVIRONMENT IN PRACTICE

This section examines successfully implemented projects of circular economy in building construction in practice. Therefore, the identified research question is:

RQ1. "How have circular economy principles been implemented in construction industry practice?"

Further research questions (RQs) that add a focus on reuse practices (the scope of this thesis) are:

RQ2. What practices are already established that implement CE in the BE?
RQ3. On which level do these practices actuate?
RQ4. Which limitations and barriers are identified?

Following the protocol presented in 3.1Methodology the search was refined to identify publications that were related to implementations in practice. To this end, the keywords "case stud*" or "project" or "practice" were added to the keywords of the initial search to refine the publications' selection. The search was conducted in Scopus, WoS and Google Scholar resulting in 17, 3 and 7 relevant papers after applying the selection criteria. Additionally, case studies were retrieved by using Search Engines (Google, Ecosia), specialized platforms such as Baunetz, organizations such as Team Zirkular and magazines, i.e. DETAIL Zeitschrift für Architektur + Baudetail. In the systematic literature research, no limit was set to the publication year. Due to time and resource limitations for translations, only English and German publications were included. The included publications and the research protocol are found in Table 56 and Table 55 in Annex II. The implemented projects are classified into micro, meso and macro depending on the implementation level.

The current method used for demolition and core removal does not enable the damage-free recovery of functional components and elements. Consequently, in most cases the economic viability of reusing extension components is limited during the entire process chain of dismantling, reworking, storage, and sale. (Dechantsreiter et al., 2015, p. 31)

3.3.1. MICRO-LEVEL

The Micro Level includes all projects that operate at the material or component level. At the micro level, therefore, components and materials are to be named that successfully implemented CE strategies. Due to the focus of this work on component reuse, the selection presented here will be limited to this accordingly.

Successfully reused components

The research project focused on reusing concrete elements from modular "Plattenbau" (prefabricated panel) buildings from the 1960s-190s in the construction of single-family and multi-family houses (Heyn et al., 2018, p. 1). In their project, they exploited the standardization of concrete elements, including walls, floors, and ceilings. These elements were designed to be easily assembled and disassembled, making them suitable for reuse. The specific construction techniques, such as the use of ring anchors and welded connections, allowed for the efficient dismantling and reutilization of the concrete components. (Heyn et al., 2018, pp. 78–79) The concrete elements were cleaned and repurposed, and pilot projects were planned in Eastern European countries such as the Czech Republic, Romania, Russia and Poland (Heyn et al., 2018, p. 1).

Romnée et al. (2019) salvaged materials such as formwork wood and reclaimed glass were used to create greenhouses. The outcome was a circularly designed greenhouse that could be easily repaired, extended, and disassembled. It had a high recycled content and was found to be significantly more environmentally friendly than an aluminum greenhouse, as shown by a comparative life cycle assessment (Romnée et al., 2019, 1).

Brütting et al. (2019) proposed a methodology for designing truss structures using reclaimed structural components, aiming to reduce environmental impact by avoiding new material sourcing and minimizing waste. The approach involves iterative element assignment, topology optimization, and geometry optimization to best utilize the available stock elements (Brütting et al., 2019, p. 128). In their case study, the main train station roof in Lausanne was designed using elements reclaimed from power transmission pylons (see Figure 28). The use of reclaimed elements and custom connection plates allowed for the reuse of elements at their full length, reducing labor and potential cutting. The study demonstrated significant reductions in embodied carbon and energy compared to weight-optimized structures using new elements. (Brütting et al., 2019, pp. 133–134)

Similarly, O'Grady, T. et al. (2021) reused steel frames salvaged from a third-party builder in their case study Legacy Living Lab (L3). In L3, the researchers investigated the interconnection methods used in designing a circular economy building to create a modular building designed for disassembly and relocation that aligns with the principles of the circular economy (O’Grady, T. M. et al., 2021, p. 1). Initially intended for recycling, the steel frames were eventually incorporated into the building with minimal redesign work. Eighteen tonnes of existing structural steel were reused in the construction. The connections of the steel frames were bolted together behind internal finishes to ensure no visible connections. This method allows for disassembly without creating waste from chemically bonded or welded connections commonly found in concrete or traditional steel structures. (O’Grady, T. M. et al., 2021, p. 7)

It is noted that only exterior components are considered here. Indoor components are the subject of the 4.1.3 What to reuse chapter.

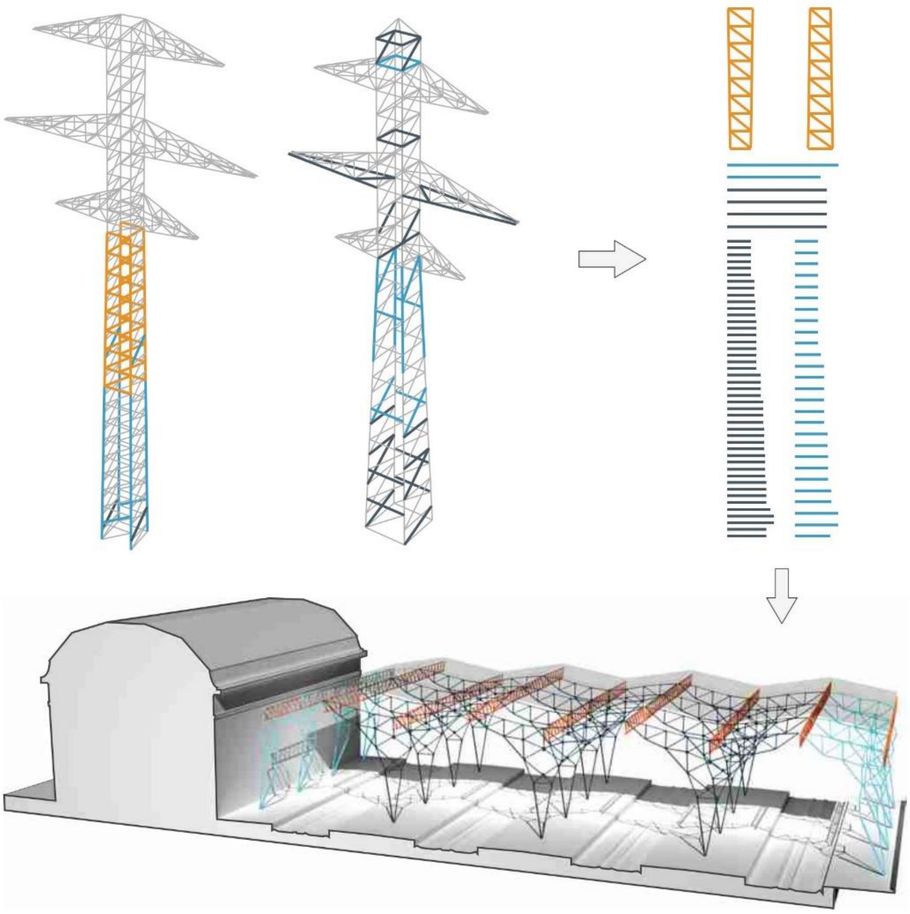

Figure 28: Schematic view of the intended roof truss design, using elements from electric pylons (Brütting et al., 2019, p. 134)

Succesfully reused materials

The most commonly tested materials for reuse in practice are bricks, glass, steel, wood, and soil (Christensen et al., 2022; Nußholz et al., 2023) This section will explore some project examples that focus on these materials.

Brick

An outstanding brick reuse project is Resource Rows, a circular housing project located in Copenhagen, Denmark, and developed and designed by the Lendager Group in 2017. This project exemplifies the concept of urban mining by utilizing various previously used building materials sourced locally. Abandoned brick facades were repurposed by cutting them into square brick modules (see Figure 29), which were then assembled as a patchwork facade for the new row houses (see Figure 30). (TU Delft)

Figure 29: Cutting process of existing brick facades (Lendager)

Figure 30: New "Resource Row" buildings with patchwork facade composed of reused bricks (Lendager)

Lozano-Miralles et al. (2018), on the other hand, incorporated organic waste in baked clay bricks and explored the environmental impacts. The study found that the incorporation of organic waste in bricks resulted in a 15-20% decrease in all studied impact categories. This indicated that the inclusion of organic waste in clay bricks is a favorable and promising approach in terms of environmental impacts, confirming the suitability of using organic additives to improve the efficiency and sustainability of bricks while reducing their environmental impact. (Lozano-Miralles et al., 2018, p. 1)

Lastly, the REBRICK project in Denmark automates the cleaning and reuse of clay bricks to handle demolition waste more efficiently. Gamle Mursten developed an innovative technology for handling demolition waste and cleaning old bricks that uses vibration to remove concrete and cement without the need for water or chemicals, making it environmentally friendly. (Gamle Mursten) By reusing bricks instead of producing new ones, it saves 0.5 kg of CO2 per brick. Through technology development and market exploration, it seeks to establish a European market for reusable bricks. (Gamle Mursten)

Soil

In the Wallasea Island Wild Coast Project in Essex, UK, the excavated material from the Crossrail project in London was recycled and reused to transform a large area of farmland back into coastal marshland. The aim was to raise land levels and create Europe's largest wetland nature reserve. (Cross, 2017, p. 3) In 2015, over 96% of the generated construction and demolition material was either reused or recycled, with around to 1.5 million tonnes of soil transported to Wallasea Island (Cross, 2017, pp. 6–8). The project exemplifies the circular economy in the built environment, where construction materials were reused in a conservation project, providing benefits for both people and wildlife (Cross, 2017, p. 3).

Timber

Timber is often reused in non-structural applications. One example of the successful reuse is the Welpeloo Villa, a private residential house, in which both steel and timber were reused. The load-bearing steel structure was reclaimed from a paternoster and textile machine, while the wooden façade cladding was made of redundant cable reels from a nearby cable factory. (Superuse)

3.3.2. MESO-LEVEL

On the meso level a differentiation is made according to the lifecyclephase in which the CE implementation takes place. Currently, applications concentrate especially on the private sector or on the renovation of historic buildings. In the commercial sector, there is still untapped potential for the reuse of building components. (Redaktionskreis Baufachliche Richtlinien Recycling, 2018, p. 58)

CE consideration in Pre-Use

Hillebrand et al. (2021) presents 21 circular new-built projects grouped according to their main circularity strategy: six case studies put an emphasis on the technical cicle in their decisions on materiality and assembly; five case studies focused on the use of biotic materials; three case studies were planned considering both the technical and the biotic cycle; three case studies used exclusively local materials, while the last four case studies put an emphasis on recycled materials.

The case studies focusing on the technical cycle, i.e. circularity strategies in architectural design, include the Musée Soulages in France (RCR Arquitectes, 2014) (see Figure 32), the Kraftwerk Lausward power plant in Germany (kadawittfeldarchitektur, 2015), the Gordola Training Center in Switzerland (Durisch + Nolli, 2011), the Dokumentationszentrum Hinzert in Germany (Wandel Hoefer Lorch + Hirsch, 2006) (see Figure 31) the extension building of The Nelson-Atkins Museum of Art in the US (Steven Holl Architects, 2007), and the Fensterfabrik Hagedorn extension in Switzerland (Graber & Steiger, 2006). Their strategies include the use of recyclable materials, such as steel and wood, modular and demountable designs, and green roofs that support local plant species and act as retention areas. The designs also prioritize flexibility and adaptability. (Hillebrandt et al., 2018, 179–190).

Furthermore, circularity strategies with a focus on the biotic cycle are employed in various construction projects. Examples of this strategy are the community center in Vorarlberg, which is constructed using locally sourced and processed wood, with no use of glued wood materials and the Wood Innovation and Design Centre in Canada, which is the country's first high-rise building constructed entirely from wood. The latter uses regional solid wood products, and composite structures are avoided to facilitate easy disassembly and recycling. A third example is a housing project in Winnenden, which employs highly prefabricated timber modules, allowing for customization and flexibility. The system reduces resource consumption and is affordable, and the modules can be reconfigured for changing needs. In all three examples, the use of wood is maximized to minimize the impact on the environment, and circularity is achieved through the reuse and recycling of materials. Finally, a private one-story house in Voralberg uses straw as both insulation and load-bearing structure, with a pre-fabricated roof module resting on stacked untreated straw bales (Hillebrandt et al., 2018, pp. 190–196).

Figure 31 Example of technical cycle considerations in architecture: Hinzert Concentration Camp Documentation Center, corten steel geometrical facade (Lange, 2006), CC BY-NC-SA 2.0

Figure 32 Example of technical cycle considerations in architecture: Musée Soulages, Rodez, France (Pierre), CC BY-NC-SA 2.0

Among the projects that considered both the technical and the biotic cycle, the first example is an office building in Austria (architekturwerkstatt Bruno Moser, 2015) a wood-based construction designed with a modular system, allowing for the efficient production of large quantities of identical elements. The second example is a temporary extension of a school building in Frankfurt, Germany (NKBAK, 2015), constructed using prefabricated room cells made of high-strength, sustainable materials, which can be easily disassembled and reused. The third example involves the refurbishment of a traditional farm building into a Wadden Sea Centre in Denmark (Dorte Mandrup, 2017) using a mix of closed-loop materials such as steel and wood. The reed roof is combined with a façade of grey-lacquered Robinia wood panels. (Hillebrandt et al., 2018, pp. 198–202)

Lastly, two building projects are constructed using materials that are either recycled or locally sourced to reduce the environmental impact of the projects. The first project is a residential and studio house "Rauch" made mostly from excavated clay and natural materials such as reed and bamboo canes, while the second project "Villa Welpeloo" (see section "Timber") from recycled and reused materials from the nearby textile industry site in Enschede, Netherlands, such as wood, metal, and EPS insulation. The steel beams in the building's structure are from an old textile machine, and the façade is made from wood boards from large cable drums. Additionally, the architects created an online platform called "Harvestmap" to map out and facilitate the regional exchange of used building materials. The use of existing materials and the short transportation distances resulted in significant resource conservation and CO2 reduction compared to conventional construction. (Hillebrandt et al., 2018, pp. 204–208).

Finally, the "Upcycle House" in Denmark explores the reuse of materials that have already had a previous life cycle, resulting in 86% less CO2 emissions during construction. The "Museum Folkwang" in Germany uses a glimmering pavilion made from recycled glass shards sintered to form a material known as "glass-ceramic" for its façade. The "Kulturinstitut" in Germany repurposes bricks from the nearby environment for its exterior and utilizes a roof structure that can be easily disassembled and reused. (Hillebrandt et al., 2018, pp. 210–213)

To conclude, the K.118 project reused existing building components from demolition sites. The project aimed to minimize waste and maximize resource efficiency by collecting and cataloging various reclaimed materials, including steel beams from the former Coop distribution center in Basel, granite facade plates repurposed as balcony flooring, aluminum-insulated windows, and red facade sheets from Winterthur and Zurich. Natural materials such as wood, straw, and clay were also consciously incorporated into the design. The K.118 project achieved a 60% reduction in the environmental footprint compared to a conventional new construction. (baubüro in situ ag, 2021)

Figure 33 Example of technical and biotic considerations in architecture. Wadden Sea Centre, Ribe, Denmark; (CC BY-SA 4.0) (Dahlstrøm Nielsen, 2017)

Figure 34 Example of a new construction reusing components. Kopfbau Halle K.118, Winterthur, Switzerland (image by author)

CE consideration in post-Use-phase

Christensen et al. (2022) carried out a case study on the island of Bornholm, Denmark to study the potential creation of a closed-loop production and consumption value chain for construction and demolition waste. The procedure of these cases comprised a pre-demolition audit, selective demolition activities, a market analysis and calculation and cost calculation, and the calculation of the CO2 reduction potential. The pre-demolition audit conducted by the municipality before each demolition included a resource mapping of materials for reuse and an environmental screening for hazardous materials. The pre-demolition audit is furthermore compared to the actually allocated materials for recycling after the demolition. (Christensen et al., 2022, p. 4) The case studies indicate that selective demolition can be economically viable if local markets for reused construction materials are established at the same time, and that certain materials, such as bricks, are more likely to form the basis of viable business models due to their uniformity, while other materials are more challenging to develop functional business cases for. (Christensen et al., 2022, p. 8)

Another example of CE interventions in the end-of-life phase is the "Areal Wolf" project in Basel, Switzerland, commissioned by the Swiss Federal Railways (SBB). It demonstrates the planning process of an urban mining project, to showcase the material and financial potential of repurposing unused infrastructure objects on a 16-hectare site. In this process, an as-built BIM model was created using 3D laser scans and a component catalog was developed in parallel to meet the requirements of deconstruction companies and architects, with building elements classified according to the Swiss element-based construction cost plan for building construction (e-BKPH) and the OEKOBAUDAT platform defined as the data source for material parameters. The component catalog only includes reusable components with circularity properties of dismantlability and modularity, which are classified based on the deconstruction effort and detachability of connections, according to the C2C categories of the Building Circularity passport.[4] The urban mining potential was expressed as a weighted percentage of reusable building components, which were determined using the BIM model.

[4] The Building Circularity Passport® is a planning and documentation tool that facilitates the circulation of a building by collaborating with architects, planning disciplines, and construction firms, providing information on material separation, chemical composition, and monetary value, offering added value for financing, risk assessment, value determination, and building operation. EPEA Netherland BV .

3.3.1. MACRO-LEVEL

It is noted that at the macro level the fewest projects were implemented. This is mainly due to the deficits in laws and regulations described in the previous section (3.2.4). National or international regulations for advancing CE and BE have been adopted at the policy level. In this context, the European Circular Economy Action Plan and the Circular Economy Promotion Law in China are worth mentioning. However, these regulations are not established in the construction practice yet.

At the macro level, nationally and supraregional operating companies and building material exchanges can also be considered. In Germany and Europe, there are already many business models that specialize in the selling of building components. In Germany, notable online platforms for component reuse include Concular, Restado, and Bauteilnetz. Additionally, the Kleinanzeigen second-hand platform offers a wide selection of reclaimed components. In Switzerland, SALZA and useagain are established reuse platforms. Furthermore, the platforms Opalis (Belgium), Environmate (UK) and Excess Material Exchange and Oogskart (Netherlands) also focus on the collection and mediation of components are carried out for both private consumers and with a focus on planners and architects. Some of the component exchanges mentioned will be used as a basis for investigation in the next chapter.

3.4. MACHINE LEARNING AS ENABLER FOR A CIRCULAR BUILT ENVIRONMENT

In this chapter the state-of-the-art regarding Machine Learning as enabling technology for the CE implementation in the CI is presented.

3.4.1. METHODOLOGY

The aim is to answer the research question:

RQ1. How can ML enable the transition towards BE?

In addition to the research regarding ML for CE in BE gathered by Çetin et al. (2021) and ML in the AEC sector gathered by Darko et al. (2020), this thesis focuses on ML techniques that specifically enable the component reuse and thereby also considers ML applications that have been implemented in the AEC sector and that are potentially useful for component reuse. Therefore, these research questions need to be addressed:

RQ2. How has ML been used in the AEC sector?
RQ3. How has ML been used for CE implementation?
RQ4. Has ML already been used for component reuse?

Based on the contribution of previous publications it is examined which results can be taken up and further developed. Furthermore, a literature research is conducted to detect potential intersections between research on artificial intelligence and strategies of circular economy in the construction industry.

The research protocol and the included publications can be found in Table 57 and Table 58 respectively in Annex II.

3.4.2. RQ1. HOW HAS ML BEEN USED IN THE AEC SECTOR?

Darko et al. (2020) conducted a comprehensive scientometric study that analyzed 41,827 bibliographic records to provide a systematic and quantitative analysis of the state-of-the-art research on AI-in-AECI (independently of their usefulness for CE). The study found a growing interest in research applying AI techniques/algorithms/concepts to AEC problems during the last decades since its emerging in the 1970s. (Darko et al., 2020, p. 12) Based on the results, it can be concluded that the most often used AI techniques in the AEC community have been genetic algorithm (GA), neural networks (NNs), fuzzy logic (FL), fuzzy sets (FSs), and ML; while the most widely addressed topics/issues using AI techniques/concepts include optimization, simulation, uncertainty, project management, and bridges. (Darko et al., 2020, p. 4) The scientometric analysis showed that topics such as robotics, energy, thermal comfort, life cycle cost and LCA did not receive much attention. (Darko et al., 2020, p. 12) Overall, according to Darko, Chan et al. (2020) the deployment of GA for optimization problems (e.g., schedule optimization or cost optimization) has been the most common AI application in the AEC industry. (Darko et al., 2020, p. 4). Despite being a prominent topic in the literature, only a few of the many techniques available in machine learning, such as neural networks (NNs) and support vector machines (SVMs) are employed in AEC, while others like naive Bayes, Gaussian mixture, and reinforcement learning, are not. (Darko et al., 2020, p. 5) Furthermore, CNNs have only recently been categorized and utilized as vision and learning-based techniques in the AEC field to address problems such as damage detection, facility operations and management, monitoring safety on construction sites, estimating concrete compressive strength, performing structural health monitoring (SHM), making decisions based on maximum gradient (MG) among others. (Darko et al., 2020, p. 13) In damage detection, the detection of cracks in concrete has been a focus area. Darko et al. (2020) suggests research and development (R&D) efforts to be directed toward how to integrate robotics and other AI methods with the topics of energy, thermal comfort, life cycle cost, and LCA; leaving circularity topics such as reuse, and disassembly disregarded.

Machine learning is used in building design and optimization to formulate design problems and analyze the optimality of the building design. It is also used to identify complex design parameters according to specific criteria such as minimum embodied energy and carbon (EEC) and cost. In addition, generative adversarial networks (GAN) have been used to generate new architectural solutions, including floor plans and entire buildings, to benefit the design of energy-efficient buildings. However, there are still some limitations, such as the need for massive amounts of training data that need to be addressed to extend the applicability of these methods in building performance optimization. (Gan et al., 2020, pp. 13–14) In the literature study it is noticeable that the usage of machine learning in the AEC sector is fragmented, with a huge research focus on assessment and prediction of environmental impact and the management of construction demolition waste, as well as the progress monitoring.

3.4.3. RQ2. HOW HAS ML BEEN USED FOR CE IMPLEMENTATION?

Cetin et al. (2021) analyze of the intersection of the three fields— circular economy (CE), the built environment (BE) and digital technologies (DTs) by offering an integrative review of these domains. The paper identified artificial intelligence (AI) as one of ten enabling DTs and examined its potential role in a circular BE across the buildings' life cycle stages. The publication proposes a Circular Digital Built environment (CDB) framework that links the identified DTs to circular building strategies. (Çetin et al., 2021) It is therefore a valuable starting point for the research on artificial intelligence and machine learning, the focus of this thesis. Aligning with research trends according to Darko et al. (2020), the enabling functions of AI were grouped into their use in design optimization, in prediction of defects in systems and determination of resource needs in buildings in combination with other technologies, and in end-use phase activities (Çetin et al., 2021). Furthermore, papers in the field of building stock analysis were identified. Some of the research topics will be further discussed below.

Design optimization

Duan et al. (2022) developed a set of AI technologies to promote sustainable reuse of urban ruins. The technologies used in the study include sentiment analysis and Generative Adversarial Networks (GAN) technology. The sentiment analysis technique was used to pre-evaluate public willingness around urban ruins and guide the reuse of ruins, while GAN technology was utilized in the schematic design phase to identify site information and evaluate building performance and value for sustainable reuse. The study also proposes the use of intelligent building and landscape design, services, and management to make the reuse of urban ruins more energy-efficient, environmentally friendly, and intelligent. (Duan et al., 2022) Ploszaj-Mazurek et al. (2020) developed regenerative design guidelines and trained a ML model to predict the optimal building features. This model was used as prototype for an application, which was later updated with a new algorithm to predict the Total Carbon Footprint of a building design based on basic building features and the urban layout. The study demonstrated the potential for introducing Carbon Footprint estimation and building optimization in the initial design phase. (Płoszaj-Mazurek et al., 2020) Huang et al. (2021) present a review and comparison of algorithmic formulations for reuse-driven design in computational approaches. They introduce a new Grasshopper tool that implements these formulations and utilizes the Hungarian Algorithm in a nested loop workflow to achieve flexible design space exploration and efficient optimization. The tool allows real-time computation of material reuse efficiency for small problems and provides results within seconds for larger problems. (Huang et al., 2021, p. 10)

Prediction and detection of defects

First, Cha al. (2017) propose a vision-based method using convolutional neural networks (CNNs) for detecting concrete cracks in civil infrastructure without relying on traditional image processing techniques. The trained CNN, combined with a sliding window technique, demonstrates high accuracy and robustness in detecting cracks in images of varying resolutions and challenging conditions. (Cha et al., 2017, p. 361) Similarly, Alipour et al. (2019) developed a deep fully convolutional neural network called CrackPix for pixel-level defect detection in concrete infrastructure. The model is trained on a carefully annotated dataset and achieves high accuracy in detecting crack pixels. CrackPix outperforms patchwise models and traditional methods enabling the quantification of crack characteristics (e.g., width and length) in concrete structures, and showing its potential for automated inspection and quality assurance in smart cities. (Alipour et al., 2019, p. 1)

End-of-use-activities: Waste

Akanbi et al. (2020) developed deep learning models to predict the amount of salvage and waste materials obtainable from buildings at the end-of-life prior to demolition. The models achieved high accuracy in predicting *material recovery* based on basic building features, providing decision support for demolition engineers and waste management planners (Akanbi et al., 2020, p. 1). Lau Hiu Hoong et al. (2021) developed a faster and automated method for determining the composition of recycled aggregates (RA) using deep learning and achieving a 97% accuracy in identifying the nature of the RAs. Additionally, the study proposed a method for estimating the mass of grains and explored the automatic extraction of grains from RA images using Mask R-CNN. (Lau Hiu Hoong et al., 2021, p. 1) Similarly, Davis et al. (2021) used deep learning models to automatically classify waste into four categories (organic waste, glass, metal, and plastic) using the self-generated OrgalidWaste dataset. This automated waste classification method has potential applications in the waste management sector to improve efficiency and reduce manual labor. (Davis et al., 2021, p. 1)

Building stocktaking

Platten et al. (2020) used machine learning methods to enhance the Swedish database of Energy Performance Certificates by adding building characteristics necessary for assessing the feasibility of energy retrofitting packages. The study focused on multifamily buildings constructed between 1945 and 1975. Ocular observations in Google Street View were conducted to gather data on building type and suitability for additional façade insulation. The results demonstrated that these characteristics could be predicted with high accuracy. The study concludes that machine learning has the potential to enhance building databases for energy retrofitting assessments, leading to improved estimations of national energy savings potential (Platten et al., 2020, p. 1)

3.4.4. RQ3. HAS ML ALREADY BEEN USED FOR COMPONENT REUSE?

In this chapter RQ3. *Has ML already been used for component recognition?* is answered: In the rapid review a selection of nine papers explicitly focusing on the application of machine learning for the reuse of components were identified, while two papers were added manually. The included publications are found in Table 59 in Annex II.

In the field of urban stock analysis, Raghu et al (2022) conducted ocular observations using Google Street View to analyze two building-specific characteristics: (1) façade material and (2) reusable components (window, doors, and shutters) found on building facades in two cities: Barcelona and Zurich. The scheme explores the use of the state-of-art neural network Mask R-CNN for window detection but does not analyze further characteristics. The data collected is used to create classification maps that can help define protocols and for urban planning. This research can upscale limited information in countries where available data about the existing building stock is insufficient. (Raghu et al., 2022, p. 577)

Gordon et al. (2023) conducted a case study that showcases the use of accessible technology (Lidar and 360° images) for capturing site data to support the digitization of steel structural building stocks for circularity purposes. The study focuses on adapting Scan-to-BIM processes to create digital models of demolition sites, enabling better planning for deconstruction works and maximizing the value of recovered materials. Specifically, the reconstruction of steel column and beam systems is emphasized, addressing the challenges of accurate capture and inter-element relationships. Low-cost 360° cameras are identified as the most viable technology for capturing reliable information, while mobile Lidar systems require further development. The development of these technologies is considered crucial for integrating digital solutions into existing workflows. The Scan-to-BIM tools are considered a logistical foundation for conducting complex reuse analysis and facilitating connections between actors in the circular economy ecosystem. (Gordon et al., 2023, pp. 13–14)

While the aforementioned publications enable the component reuse by identifying the components, none of the machine learning applications decides upon the reusability itself. In this context, publications of a series of studies authored by Rakhshan et al. (2021a, 2021b) are noted, that aim to provide a set of interdisciplinary predictive tools to assess the technical, economic, and social reusability of a building's structural components (Yeung et al., 2015). Firstly, Rakhshan et al. (2021a) developed a probabilistic predictive model using advanced supervised machine learning methods to evaluate the economic reusability of load-bearing building elements. The study used a systematic literature review to create an online questionnaire survey to identify factors that determine the reusability of load-bearing components. The survey results are then converted into a binary response, with zero indicating non-reusability and one indicating reusability. Finally, based on the feature selection to identify relevant variables for the classification problem of predicting economic reusability, 13 different prediction models were developed and evaluated. (Rakhshan et al., 2021a, pp. 5–9) The study concludes that the approach developed could reliably estimate the economic reusability of these elements based on affecting variables (Rakhshan et al., 2021a, p. 2).

Using the same methodological approach as in (2021a)(Rakhshan et al., 2021a), a second study intends to develop a predictive model to estimate the technical reusability of the structural elements at the end-of-life of a building (Rakhshan et al., 2021b, p. 5). The study identifies and ranks the main reusability factors based on stakeholders' experiences and develops an easy-to-use learner for practitioners to assess the technical reusability of load-bearing components. The most crucial factors affecting the reuse of building structural components are design-related, such as matching the design of the new building with the strength of the recovered element, and the presence of hazardous or contaminating coatings. Another identified barrier is a potential problem with collateral warranties, which requires further research to overcome. (Rakhshan et al., 2021b, p. 10)

3.5. STUDY LIMITATIONS

The literature study and consequently its content analysis are objected to certain methodological and representative limitations.

Firstly, the keyword search used to identify relevant articles may have limited the results to the author's selection and specific combinations of keywords: The study only includes articles with the term CE and BE in their title, abstract, or keywords, which may not encompass all relevant literature. The keywords search may ignore important synonyms and could have been expanded to include additional terms such as "civil engineering", "recycling", "further use" or "repair".

Secondly, the search was limited to the digital databases and to English publications, potentially missing relevant materials published in other languages or available in other data collections.

Third, the literature review has a narrow scope and restricting inclusion criteria, because of time and resource limitations within the diploma thesis. As a consequence of these limitations, this thesis concentrated on review papers. The presented literature study largly depends on the selected reviews' quality and scope. In addition, the literature synthesis is based on the author's interpretation and, thus, includes the possibility of a researcher's bias in the selection of articles despite the established inclusion criteria. On the other hand, the selected reviews represent broad and current areas of knowledge due to the author´s publication experience and the recent date of publication of the selected reviews.

Additionally, the selection of papers from academic journals in the construction industry may not have captured the latest industry.

Finally, it is important to note that the list of included practice examples and the studies of machine learning application for component reuse presented in this research are not exhaustive. The findings and conclusions drawn from these studies may not encompass all possible scenarios and developments within the field.

4 METHODOLOGY

In this chapter the methodology for the machine learning algorithm is established. Therefore, in the first section the necessity of component reuse is highlighted and the properties upon which the reusability is dependent are presented as “reuse criteria”. Furthermore, the process of component reuse is presented and established practice frameworks are reflected on. Drawing on these processes and the importance of the reuse process optimization, in the second section the scope of the machine learning algorithm is defined, and appropriate techniques are considered. Finally, specific machine learning algorithms are selected for the implementation.

4.1. ESTABLISHMENT OF REUSE CRITERIA

4.1.1. WHY TO REUSE

There is an urgent need to transition towards a circular economy in the AEC sector as outlined in previous chapters. Reuse is considered the most important among the end-of-life-strategies (see 2.1.1 CE Principles in the AEC sector) in the waste hierarchy (European Council and European Parliament, 2008, p. 8), which constitutes one of the underlying core concepts of the CE (Purchase et al., 2021, p. 6).

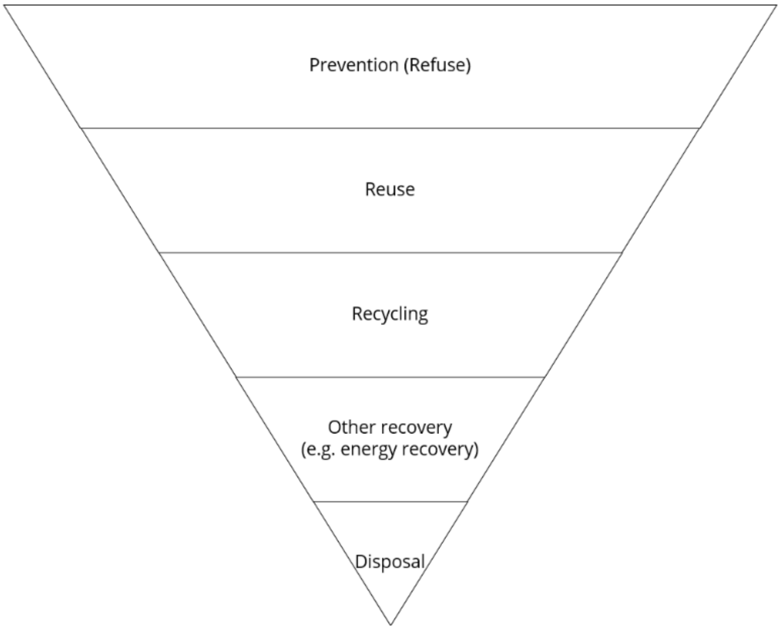

Figure 35 Waste hierarchy acc. to the Directive 2008/98/EC (image by author)

One of the main opportunities is to prevent outgoing materials during building renovation or deconstruction from becoming waste by increasing the reuse rate (Tirado et al., 2022, p. 13) Currently, building materials and components are considered as waste when they are no longer needed for the planned function, which accelerates the devastation of ecosystems, increases environmental costs and entail risks of resource scarcity (Munaro et al., 2020, p. 3). Therefore, reusing materials is an important closing-the-loop strategy as it allows for the recirculation of recovered resources in the life cycle, which can be used in new construction applications instead of relying on virgin raw materials. Material reuse is a way to extend the life cycle of building materials, promoting sustainability in the construction industry (Ginga et al., 2020, p. 5). Also, by reusing materials, the amount of waste generated can be reduced, and the environmental impact of producing new materials can be minimized (Charef et al., 2021; Ginga et al., 2020, p. 5).

According to Addis (2007, p. 5) next to the environmental reasons the generation of advantages for building initiatives (such as obtaining planning authorization or lowering expenditures), and the credibility enhancement of individuals involved in building construction are reasons for the recovery and reuse of products and materials. Accordingly, reclamation, reuse, and recycling can benefit building projects by adding value, but it may not apply to every project. Some common reasons include avoiding demolition costs, reducing landfill expenses, gaining planning permission by matching the new construction to materials and methods in adjacent buildings, using cheaper reconditioned equipment, gaining environmental impact credits, and showing a commitment to reducing the environmental impact of construction. (Addis, 2007, p. 7) Furthermore, organizations are competing to appear more environmentally conscious, and their reputation in environmental matters can affect various aspects of business. In the construction industry, a good environmental record can affect the ability to get work or sell goods/services, and using recycled materials can demonstrate a commitment to the environment. (Addis, 2007, p. 9) Furthermore, it is becoming apparent that legislation will provide for stricter regulations and interpretations of the circular economy in the future to meet common goals, such as the Sustainable Development Goals. Companies that incorporate CE strategies such as reuse early are deemed to have a prospective competitive advantage.

4.1.2. HOW TO REUSE

The lack of standardization is one of the major barriers in the implementation of CE strategies in the AEC sector (see previous chapters). The circular economy (CE) in construction is missing a comprehensive framework for evaluating the degree of circularity in projects, which hinders the industry's ability to restructure and fully transition to a circular economy. (Abadi et al., 2022, p. 4) In literature several frameworks for the implementation of CE are proposed (Antwi-Afari et al., 2021; Çetin et al., 2022; Ginga et al., 2020; Hossain et al., 2020b), however on the meso (building) and micro (components and materials) level reusability assessment methods are exceptional. In a previous work, the author reviewed various sustainability certification systems in terms of their informative value about the circularity of buildings and their components. The results align with Anastasiades et al. (2020) and Rosen (2020) in that these certification schemes so far only consider circularity to a limited extend and are yet inappropriate for a full-scale circularity evaluation. Furthermore, they do not include frameworks for assessing the reusability of building components. Hence, the conduction of the reuse process is not uniform, resulting in differing project dependent approaches.

However, the planning process in the considered case studies (see 3.3) and the literature (Angst, 2021; John and Stark, 2021; Raghu et al., 2022) coincide in their base structure. Therefore, drawing on a previous work of the author (Bendiek Laranjo, 2022) and the results of the literature studies an optimized planning process is proposed in Figure 36.

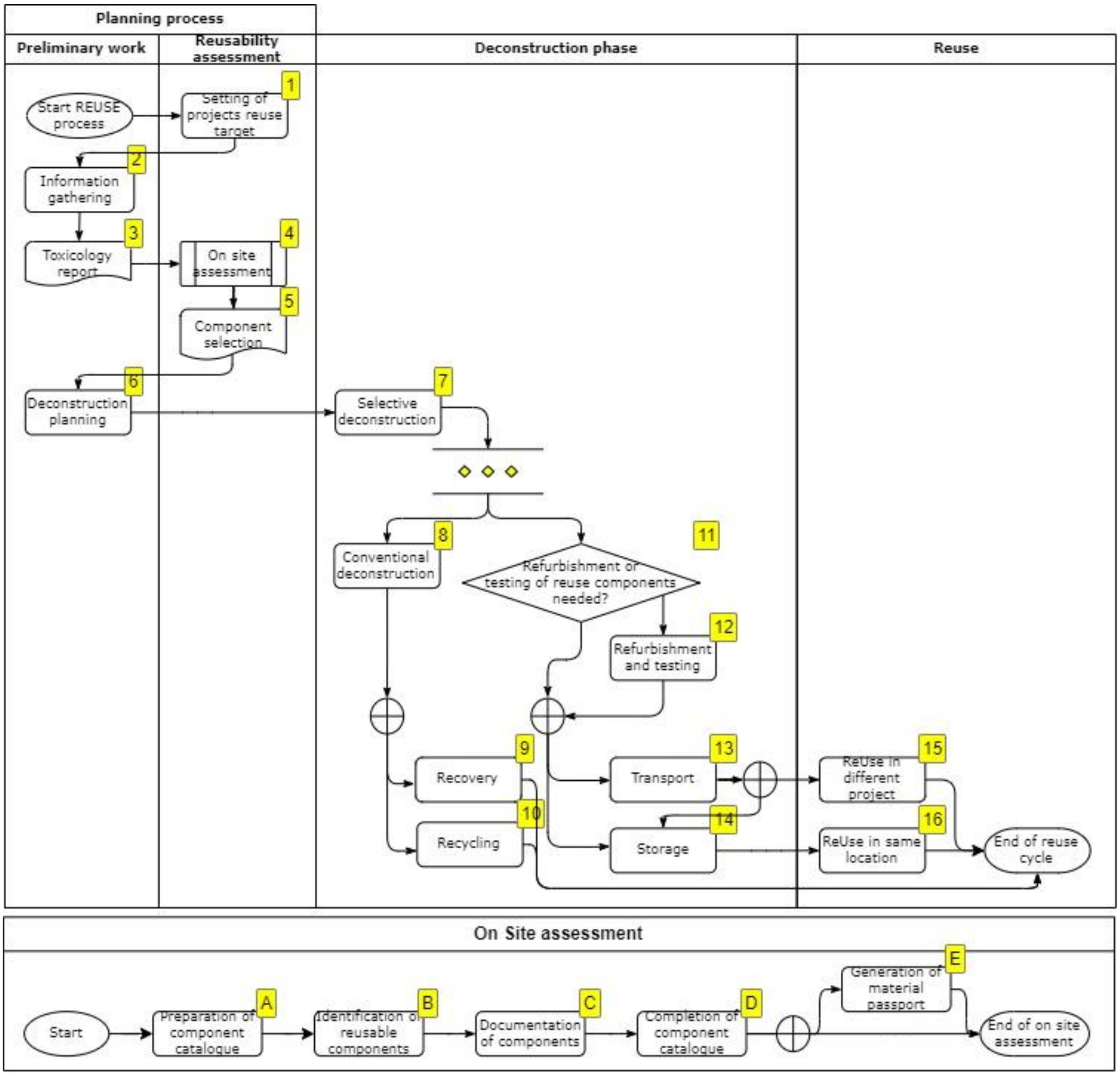

Figure 36 Cross functional diagram of the reuse process (image by author)

According to Figure 36 the reuse process comprises the following steps:

(1) **Setting projects reuse target**.

In general, two approaches are observed in practice: the maximization of reuse (exploitation of the urban mining potential) and the pre-selection of reusable components. The first approach is often based on the client's wish to demonstrate through the project what economic and ecological potential urban mining offers for their own company. Often, these are pilot projects based on an exemplary building from a homogeneous portfolio, so that results can be extrapolated to the other assets. This approach therefore identifies the maximum number of components for reuse, regardless of whether their reuse is already firmly planned in a project or even whether a potential customer exists. An example of the first approach is the Areal Wolf in Basel, Switzerland, in which the SBB sought to uncover their Urban Mining Potential. In the second approach, the target projects for the reusable components are usually determined, i.e., that designs for circular projects are available for which specific components have to be found. An example for this type of project is the Kopfbau Halle K118 in Winterthur, Switzerland.

(2) **Information gathering**

The gathering of building information is the key process of the preliminary work, as the information constitutes the basis for both the toxicology report as well as the reusability assessment. Since a large number of existing buildings were neither designed circularly nor backed up by digital material information (in form of material passports or BIM models), the rebuilt of EoL datasets of these buildings can be time-consuming, incomplete, and even inconsistent (Yu, Yazan et al., 2022, p. 11). A good reference for evaluating and describing building fabric is provided in the Building Code Recycling in the form of checklists, data sheets, and technical specifications (Redaktionskreis Baufachliche Richtlinien Recycling, 2018, p. 89). Accordingly, the targeted information sources include building permits, operating manuals, site plans, floor plans and section views, archives of the owner/building authority/user, heritage protection etc. (Redaktionskreis Baufachliche Richtlinien Recycling, 2018, pp. 90–91), and as-built documents such as static and building physics calculations, maintenance and utilization records, documents on (de-)construction measures, existing expert reports/technical investigations/rehabilitation documentation, information on exceptional incidents such as fire damage, accidents, etc. (Dechantsreiter et al., 2015, pp. 45–46) and invoices. However, public building registries typically gather data on overall building features such as size, height, and number of floors, yet crucial information on building components remains absent (Raghu et al., 2022, p. 578). In addition, a risk to be considered is the deficiency of the as-built data of the existing buildings including incorrect measurements and deficient structural details (Uotila et al., 2021, p. 250). To obtain sufficient data on the building stock for the deconstruction planning, laser scanning (LS) and 360 imaging technology are popular tools, which enable the creation of BIM models and the identification of component characteristics within already constructed buildings (Raghu et al., 2022, p. 578).

(3) **Toxicology report**

The third step is the preparation of the toxicology report, a prerequisite for any deconstruction project. *Pollutants must always be removed from the existing structure first and disposed of separately before any demolition can begin - the same applies in the case of re-use (Hillebrandt et al., 2018, p. 11).* In simple terms, it can be said that components contaminated with pollutants are not eligible for reuse (Rosen, 2020, p. 90).

(4) **Onsite assessment:**

The onsite assessment, also referred to as pre-demolition audit, comprises the actual building inspection and the reusability assessment, and results in a component catalogue.

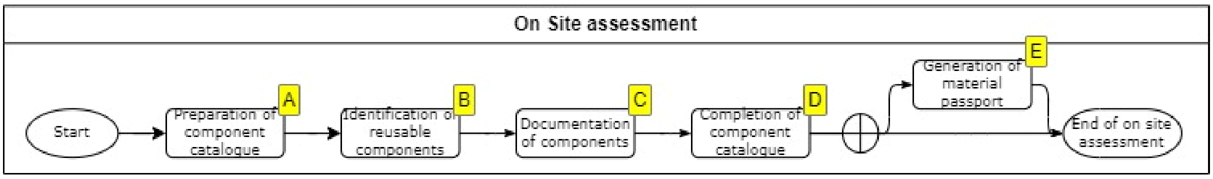

Figure 37 Process diagram of the onsite assessment (image by author)

A. *Component catalogue concept*

The component catalog defines the properties that are necessary for subsequent reuse. The properties must sufficiently precisely describe the component for its potential reuse or further use. The field research in section 4.1.3, What to reuse, provides architecturally relevant properties based exclusively on real RMMs and case studies. These properties serve as a planning foundation and can be categorized as necessary and optional component properties.

Table 10 General building component properties for reuse planning.

Mandatory properties	
Property	Data format
component name	alphanumeric
component type	alphanumerical
height	numeric
depth	numeric
width	numeric
material core	alphanumeric
material surface	Alphanumeric
quantity	numeric
unit	alphanumeric
condition	alphanumeric
Optional properties	
Fabrication year	numeric

For a uniform categorization of building components, reference to standards is suggested. For example, in Germany, the components should be named in accordance with the DIN276 Building costs, and in Switzerland according to the eBKP-H (element-based building costing plan).

Despite their growing importance, there are currently no reliable, practical, and user-friendly methods available for calculating the service life of components. One reason for this is the insufficient availability of data on the service life of components. (Bahr and Lennerts, 2010, p. 6) In Germany the durability or the technical service life is determined according to the "Service life of components" table of the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR) (BBSR, 2017).

However, some building components have additional type-specific properties that are necessary for the determination of their reuse (but not for further-use, as further-use implies a change in function). Component specific properties are shown in Table 11 and Table 12 using the example of Doors and Windows.

Table 11 Type-specific properties: Doors

Mandatory properties		
Property	Data format	Example
Location	alphanumeric	Indoor, outdoor
Frametype	alphanumeric	surround frame, corner frame, block frame
Opening type	alphanumeric	DIN left, DIN right, sliding door, folding door, segment door, revolving door, pivot door
Locking	Alphanumerical	Details of locks or locking and access mechanisms and required keys, electronic cards, and their number
Fire protection	boolean	True/false
Smoke protection class	alphanumeric	
Thermal protection	Alphanumeric	
Sound protection	Alphanumeric	
Burglary protection	Alphanumeric	
Motorized, electronic opening	Boolean	
Optional properties		
Property	Data format	Example
Fitting types	alphanumerical	hinges, handles, lever handles
Sensors	Boolean	True/false
Spies	Boolean	True/false

Table 12 Type-specific properties: Windows

Mandatory properties		
Property	Data format	Example
Location	alphanumeric	Indoor, outdoor
Frame material	alphanumeric	Wood, aluminum, plastic, steel
Glazing type	alphanumeric	Single, double, multi glazing
Isolation	Boolean	True/false
U-value	Numerical	Ug-value > 1,3-1,1 (W/m2K) to comply with legal energy saving requirements (Dechantsreiter et al., 2015, p. 54)
Sash type	alphanumeric	DIN left, DIN right, sliding door, folding door, segment door, revolving door, pivot door
Locking	Alphanumerical	Details of locks or locking and access mechanisms and required keys
shading	Boolean	True/false
Shading type	alphanumerical	Inter-pane space; external, internal
Fire protection	Boolean	True/false
Smoke protection class	alphanumeric	
Thermal protection	Alphanumeric	
Sound protection	Alphanumeric	
Burglary protection	Alphanumeric	
Motorized, electronic opening	Boolean	
Optional properties		
Property	Data format	Example
Fitting types	alphanumerical	hinges, handles, lever handles
Sensors	alphanumeric	

Furthermore, in practice the component catalogue is mostly created analogously or in Microsoft Excel, which can be explained by the non-existence of corresponding tools.

B. Identification of reusable components:

The identification of reusability is the most complex part of the urban mining process and depends on a series of component properties. Most case studies and publications, including the present thesis, narrow the scope to a component selection whose reusability has been experimentally or experientially validated, and do not examine the reusability itself. This can be explained by the current lack of a widely accepted method or standard for systematically evaluating the reusability of building elements and structures (Carvalho Machado et al., 2018; Hopkinson et al., 2019; Hradil et al., 2017, p. 4512; Rakhshan et al., 2020). Still, in research assessment methods for specific components can be found: Hradil et al. (2017) introduce an approach based on indicators to assess the reusability of components and structures of steel-framed buildings (Hradil et al., 2017, p. 4512).

In literature, to the author's best knowing, two general, component-independent reusability assessment methods exist: the systematized questionnaire proposed by Carvalho Machado et al. (2018) and the Urban Mining Index proposed by Rosen (2020).

In their paper, Carvalho Machado et al. (2018) equate the potential for deconstruction with the potential of reutilization of construction materials. The possibility of recovering building materials depends on how a building was designed and constructed, and on the deconstruction technique that is applied at the building's EoL. Therefore, researchers developed guidelines to enable and facilitate the deconstruction summarized as "Design for Deconstruction" (DfD) or "Design for Disassembly".

In their paper, Carvalho Machado et al. (2018) equate the potential for deconstruction with the potential of reutilization of construction materials. However, as the possibility of recovering building materials depends on how a building was designed and constructed, and on the deconstruction technique that is applied at the building's EoL, researchers developed guidelines to enable and facilitate the deconstruction. These guidelines are formulated as "Design for deconstruction" (DfD), which is also known as "Design for disassembly". In their paper, Carvalho Machado et al. (2018) present an analysis of DfD guidelines for the identification of characteristics that are influencing the reutilization process of components from a building at the end of its lifecycle. Carvalho Machado et al. (2018, pp. 1–2) analyze these DfD guidelines for the identification of characteristics that are influencing the reutilization process of components from a building at the end of its lifecycle. The influencing parameters were categorized into the groups "direct influence"; "impact on the ease of the process" and "influence in terms of extending the lifecycle" as seen in Annex III (Carvalho Machado et al., 2018, p. 6).

Furthermore, Carvalho Machado et al. (2018) provide a tool in the form of a questionnaire for each of the three groups to assess the reusability of building components. These questionnaires determine which criteria lead to the exclusion of degradability and which have a positive or negative effect on it, and thus, enable the evaluation of the reusability of building components. However, according to the author of this thesis, the tool has the following limitations: Firstly, it does not explain the order of the questions, although it is recommended to prioritize characteristics that lead to direct exclusion for efficiency reasons. Secondly, the tool uses Boolean questions, which are easy to handle, but due to the qualitative nature of the questions, require a certain level of expertise. Therefore, the authors recommend providing example constructions to facilitate decision-making. However, the most significant limitation is the lack of sufficient differentiation between further use and reuse: as defined in 2.1.1 CE Principles in the AEC sector the separation of a building component into different layers with the purpose of reusing them separately, as it is considered in "Construction material separation", is considered "further-use".

Table 13 Characteristics Influencing Deconstruction Potential according to Carvalho Machado et al. (2018)

Direct influence	**Impact on the ease of the process**	**Influence in terms of extending the lifecycle**
Expected durability	Standardization and Pre-Fabrication	Standardization/pre-fabrication of construction materials
Toxicity and construction material hazardousness	Standardizing and Simplifying Connections	Standardization of connections
Possibility of reutilizing (or preferably reusing) construction materials	Modulation	Modulation
Damage caused to connected parts during construction	Technology, Machinery and Tools	Accessibility of parts and connections
Damage to connections during the process	Accessibility to Parts and Connections	Separation from other construction materials
Construction material separation	Number of Connections	Disassembly type
Space for equipment and maneuvering	Ease of Removal of Connections	Space for equipment and maneuvering
Space for correct storage of construction materials	Expected Durability of Connections	Built environment flexibility and adaptability
Risk assessment and adoption of security measures	Disassembly Type	
Disassembly procedure	Disassembly Method	
As-built drawings	Construction Material Identification System	
DfD strategies adopted at the design stage	Information System for Construction Materials Used	

The second methodology is the Urban Mining Index (UMI), as proposed by Rosen (2020). The UMI proposes is used to measure and assess the circuit consistency of building structures in new construction design, which takes into account the circularity potential of materials by incorporating parameters such as material quality, and the economic and constructive viability of selective dismantling (Rosen, 2020, p. 10). The parameters must be based on the life cycle approach, consider both the material and constructive level, and include economic aspects. Both qualitative and quantitative parameters are needed for a differentiated evaluation (Rosen, 2020, p. 89). It is noted that the parameters assess the circularity of components including not only the reuse but also the other "R"-potentials (recycle, recovery). In Table 14 (see p. 80) only the selected qualitative and quantitative reuse parameters on the material and constructive level that are relevant in the post-use-phase (after building decommission) are presented.

Table 14 Reuse parameters on the material and constructive level according to the UMI (Rosen, 2020)

Material Level	
Parameter	Explanation
Absence of pollutants	Pollutants that are dangerous to humans and the environment should not accumulate in either the natural or technical cycle, and even small additions of hazardous substances can restrict recyclability, making pollutant-free building materials a prerequisite for consistent cycles. The absence of pollutants is an exclusion criterion in the UMI, meaning that if a building product contains a substance that does not meet the legal limits, the material has no circular potential. (Rosen, 2020, p. 90)
Constructive Level	
Non-destructive Detachability	The constructive level crucially determines the reuse of building materials. Dissolvable connection techniques and homogeneous separability are prerequisites for the high-quality recovery of materials. (Rosen, 2020, p. 96)

Rosen (2020) proposes the quantified expression of the circularity of buildings using the Urban Mining Index. The calculation of this index also considers the percentage of recyclable and non-recyclable materials and is therefore beyond the scope of this thesis.

Finally, based on Carvalho Machado et al. (2018)and Rosen (2020) a selection of necessary and optional properties for the identification of reuse components was compiled in Table 15.

Table 15 Identified component properties for reusability determination.

Mandatory properties		**Optional properties**	
Property	**Data format**	**Property**	**Data format**
Toxicity	Boolean	Modularity	Boolean
Type of assembly	alphanumeric		
Durability	numerical		

In conclusion, drawing on the aforementioned systems a simplified decision tree to identify reusable components during the onsite assessment is proposed in Figure 38.

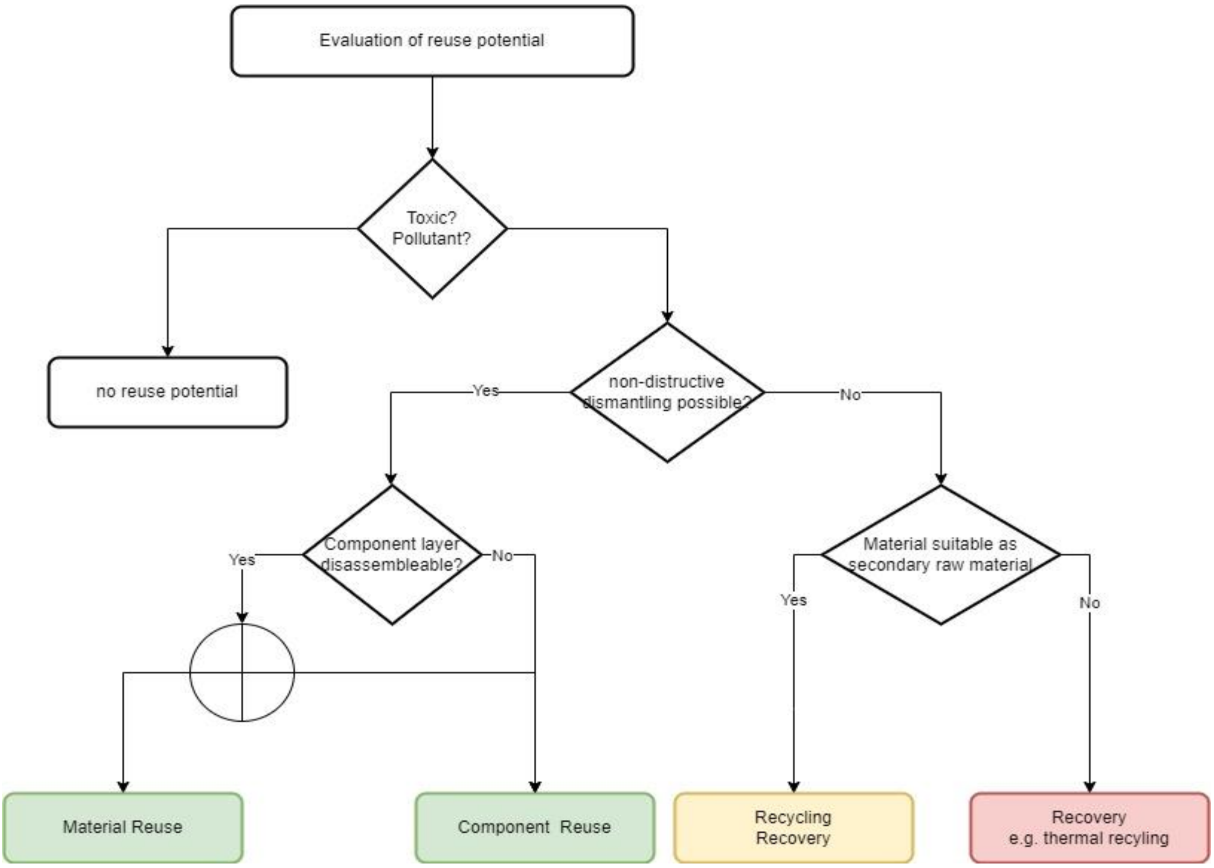

Figure 38: Process diagram for reusability evaluation of building components, image by author

It is noted that the individual responsible for conducting the diagnostic evaluation must receive adequate training to accurately recognize all materials and technical details. With their expertise, they can enhance the recovery of materials and products during the deconstruction process (Tirado et al., 2022, p. 13).

C. Documentation of components

During the assessment the properties are documented according to the component catalogue. The selected case studies have a similar approach of documentation: In general, the documentation includes taking pictures and measurements, and extracting material probes. In this thesis the case study “House of 1000 faces” in Konstanz, Germany is presented as reference:

In this case study the documentation took place once the component selection was delivered to the interim storage. In total, there were five documentation elements that were constantly updated with the progress of the design and the storage of building materials:

1. Excel table “component management” ("Bauteile Management"): contains a collection of materials with information on dimensions, location, and inventory for the current project, as well as a list of needed materials.
2. Component catalogue (“Bauteilkatalog”), sorted by the five building components with photos of materials used in the current project.

3. Component Fact Sheet (“Bauteilsteckbriefe”): contains information on important materials with images and dimensions for communication with the demolition contractor.
4. Component image: a collection of images of materials categorized by type and labeled with an index.
5. Overview list of stored components: a PDF summary of all stored materials with images and descriptions. (John and Stark, 2021, pp. 44–45)

It should be noted that in the examples the digital implementation is limited to drawing sketches in CAD programs and creating the catalog using Excel. A completely digital implementation, for example in BIM, is not yet known. The author strongly suggests a workflow that stores all the required information, both geometrical and descriptive, in a digital model to ensure data integrity and accessibility.

D. Completion of component catalogue.
E. Generation of material passports and coding

Material passports are well considered in research (Anastasiades et al., 2020; Benachio et al., 2020) and are deemed to store and provide information of components and materials for the new lifecycle. *"A material passport (also known as a resource passport or an object passport) is a term used to refer to digitally registered data sets of an object describing its characteristics, location, and history and ownership status, in a varying level of detail based on the scope in which the material passport is used. Material passports are developed at the urban, building, product and material levels, and are operated on BIM or a platform environment" (Çetin et al., 2021)*. MPs are considered an important optimization instrument during the early design stages and as material inventory of existing buildings (Honic et al., 2019, pp. 788–789). The creation of material passports for the re-use components can therefore be considered a closed-loop-strategy as it enables their seamless introduction in prospective further cycles.

Examples of different digital MPs the MPs generated in the BAMB project, an EU-project for enabling a systemic shift in the building sector by creating circular solutions (BAMB, 2019) and the platforms Madaster and Concular. While both Madaster and Concular provide digital solutions for generating material passports, Concular focusses less on new buildings and instead works more at the component level. Material passports are created for buildings approximately one year prior to their dismantling, meaning the inventory and materials of the building are digitally recorded, and in case of Concular, traced using Blockchain Technology (John and Stark, 2021, p. 36).

(5) **Component selection**

The Onsite Assessment results in a final selection of reusable components.

(6) **Deconstruction planning**

The deconstruction planning is usually conducted by the demolition company and should consider the different deconstruction methods. In the future, it is suggested to integrate lean construction methods into demolition planning.

(7) **Selective deconstruction**

While the conventional demolition process is not effective in recovering valuable materials and separating different types of recoverable materials, selective deconstruction involves reversing the building assembly process and is more targeted in recovering specific materials (Sáez-de-Guinoa et al., 2022, p. 17). The term "selective deconstruction" originally comes from pollutant removal but is now generally used for a high level of selection. In selective deconstruction, the various materials are returned or removed with a high degree of sorting prior to demolition of the supporting structure. In addition to dismantling, manual removal offers the best conditions for optimal recycling of demolition waste. (Rosen, 2020, p. 51)

(8) **Conventional deconstruction,**
(9) **Recovery**
(10) **Recycling**

Once the selective deconstruction is completed, the components that are not considered appropriate for reuse, further-use or recycling are demolished conventionally. The integrity of components is not relevant for further-use and recyclable materials since, by definition the product form will be dissolved in the recycling process anyway. Similarly, the solubility without destruction is not important for materials that will be used for energy purposes. (Rosen, 2020, p. 96) The primary goal of CE strategies is the waste reduction or prevention and therefore to minimize the extent of conventional deconstruction and eventually to completely avoid it. A circular system is envisioned where resources are repeatedly reintroduced through reuse or recycling, without any end of life and with minimal resource input (Çetin et al., 2021, p. 6).

(11) **Preparation for Reuse: Refurbishment or testing needed?**
(12) **Component refurbishment and testing**

The technical prerequisites for reuse are technical suitability and functionality, and the fulfillment of corresponding approval requirements (Redaktionskreis Baufachliche Richtlinien Recycling, 2018, p. 53). However, the reassembly of used materials is hindered by legal uncertainties, as liability and warranty concerns remain unresolved. Additionally, the construction sector lacks sufficient guidance documents on reuse and reutilization (Dechantsreiter et al., 2015, p. 32).

In Germany, there is no differentiation in the law between new and reused components. That is why, a building authority approval is required for a disassembled component before its reuse, just like for a new component. The reuse of wood components is regulated separately and is complicated by the 2002 Altholzverordnung (Waste Wood Regulation), which only addresses the recycling of wood and not its reuse, and categorizes wood according to its level of pollution, requiring a pollutant test before reuse (John and Stark, 2021, p. 27). In many instances, even with a high quantity of elements all the reused sections need to be tested to certify their properties and assure their quality (Rakhshan et al., 2020, p. 363).

(13) **Transport**
(14) **Storage**
(15) **Reuse in different project** or
(16) **Reuse in same location (but new project)**

The final stage of the reuse planning is the preparation of the next use cycle. The disassembly of the components on site and their reuse in a new project usually are usually time-delayed and spatially separated. Therefore, transport and storage need to be considered. In the German Technical guideline on recycling in construction two prioritized reuse scenarios are suggested:

1. Reuse as part of repurposing or integration into a new building object at the same location
2. Reuse in other buildings owned by the client (Redaktionskreis Baufachliche Richtlinien Recycling, 2018, p. 53)

However, when storing the components is a viable option, reuse opportunities in other projects increase*. "It is necessary to evaluate whether the space and storage method are adequate for the construction materials, or whether damage may be caused, compromising reutilization"* (Carvalho Machado et al., 2018, p. 9). Furthermore, *"the closer the storage space to where deconstruction or re-sale is taking place, the lower the environmental impact and transportation costs. The location must not affect urban areas and it must be a safe environment"* (Carvalho Machado et al., 2018, p. 9).

4.1.3. WHAT TO REUSE

The last section concluded that in general components, that are non-pollutant, non-destructively disassemble and compliant with technical standards can be considered reusable. In the limited reuse practice a selection of component types can be identified, that comply with these requisites due to their standardized assembly and whose reuse is more established. In this section these "reusable by default"-components were identified through a field search including online marketplaces, practice publications, and guidelines.

According to the German Construction Guidelines for Recycling, components suitable for reuse include paving stones, roof tiles, facade parts; steel structures (halls), wooden beam structures; windows, doors, sanitary objects, lighting systems and technical building equipment (heating and air-conditioning technology) (Redaktionskreis Baufachliche Richtlinien Recycling, 2018, p. 53).

Dechantsreiter et al. (2015, p. 53) focused on components of the interior and building envelope, whose reuse has been practically tested (building component exchanges/ bauteilnetz Germany and Association of Historical Building Material Dealers), and for which there is already a market. The selection considers interior components, i.e. components that are permanently attached to the building, but excludes, built-in kitchens, cabinets, lamps, and other furniture (Dechantsreiter et al., 2015, p. 53). Specifically, the selection includes exterior windows, doors, gates, interior doors, stairs, flooring, roof/walls, heat generators/radiators, sanitary facilities, pavements, enclosure: fences/gates and railings (Dechantsreiter et al., 2015, pp. 7–8) and describes required product and marketing properties. The online marketplaces were selected based on the research in John and Stark (2021) and using the search engine Google (see Table 16.

Table 16 Online marketplaces for reused components

Name	**Website**	**Country**
Concular	https://shop.concular.de/	Germany
Restado	https://restado.de/	Germany
Bauteilnetz	http://www.bauteilnetz.de	Germany
Ebay Kleinanzeigen	https://www.ebay-kleinanzeigen.de/	Germany
SALZA	https://salza.ch/	Switzerland
Useagain (ex: Bauteilclick)	https://www.useagain.ch/de/	Switzerland

The selection has the following limitations: only components that are considered to generate revenue are offered on online platforms, which excludes components that are reusable but need to undergo refurbishment or testing; the sellers are usually private persons or companies that offer easily and fast removable components rather than all theoretically reusable components. It is therefore, that economic reusability is not considered. The selection shown in the graphs is based on the number of articles in each category, however, in some of the marketplaces an article can include several elements. For example, in the marketplace Concular the category bricks had three articles, but each article included a sample of 100.000 bricks, that were sold as a pack.

Figure 39 Online Marketplaces' top 10 reused component. Absolute numbers of offered components (image by author)

Component selection for machine learning application

In the application of the machine learning algorithm doors, windows, radiators, sanitary objects, and lights should be identified. These five component types were chosen according to the following selection criteria in Table 17.

Table 17 Selection criteria for component identification

Selection criteria	Description
Relevance in practice	The component should be reusable per default, with little refurbishment and no testing needed.
Typology	The components should have standard features, but different configurations. Shapes and colors should differ.
Indoor	The availability of data demands a restriction to indoor components.

Electrical equipment and MEP installations are not part of the selection as performance parameters that cannot be retrieved from image data, are essential for their reuse. The necessary and optional properties for the reuse of the selected objects are shown in Table 19 to Table 21.

Table 18 Necessary and optional reuse properties: Radiators and Sanitary

Mandatory properties		**Optional properties**	
Property	*Data format*	*Property*	*Data format*
component name	alphanumeric	Fabrication year	numeric
Component types	alphanumerical	Color	alphanumeric
height	numeric		
depth	numeric		
width	numeric		
material core	alphanumeric		
material surface	Alphanumeric		
quantity	numeric		
unit	alphanumeric		
condition	alphanumeric		

Table 19 Necessary and optional features for reuse: Doors

Mandatory properties		
Property	**Data format**	**Example (opt.)**
component name	alphanumeric	
Component type	alphanumerical	
height	numeric	
depth	numeric	
width	numeric	
material core	alphanumeric	
material surface	Alphanumeric	
quantity	numeric	
unit	alphanumeric	
condition	alphanumeric	
Location	alphanumeric	Indoor, outdoor
Frame type	alphanumeric	surround frame, corner frame, block frame
Opening type	alphanumeric	DIN left, DIN right, sliding door, folding door, segment door, revolving door, pivot door
Locking	Alphanumerical	Details of locks or locking and access mechanisms and required keys, electronic cards and their number
Fire protection	boolean	True/false
Smoke protection class	alphanumeric	
Thermal protection	Alphanumeric	
Sound protection	Alphanumeric	
Burglary protection	Alphanumeric	
Motorized, electronic opening	Boolean	
Optional properties		
Property	Data format	Example
Fabrication year	numeric	1960: 2002
Fitting types	alphanumerical	hinges, handles, lever handles
Sensors	Boolean	True/false
Spies	Boolean	True/false

Table 20 Necessary and optional properties for reuse: Windows

Mandatory properties		
Property	**Data format**	**Example**
component name	alphanumeric	
Component type	alphanumerical	
height	numeric	
depth	numeric	
width	numeric	
material core	alphanumeric	
material surface	Alphanumeric	
quantity	numeric	
unit	alphanumeric	
condition	alphanumeric	
Location	alphanumeric	Indoor, outdoor
Frame material	alphanumeric	Wood, aluminum, plastic, steel
Glazing type	alphanumeric	Single, double, multi glazing
Isolation	Boolean	True/false
U-value	Numerical	Ug-value $>\ 1{,}3 - 1{,}1\ (\frac{W}{m^2K})$ to comply with legal energy saving requirements (Dechantsreiter et al., 2015, p. 54)
Sash type	alphanumeric	DIN left, DIN right, sliding door, folding door, segment door, revolving door, pivot door
Locking	Alphanumerical	Details of locks or locking and access mechanisms and required keys
shading	Boolean	True/false
Shading type	alphanumerical	Inter-pane-space; external, internal
Fire protection	boolean	True/false
Smoke protection class	alphanumeric	
Thermal protection	Alphanumeric	
Sound protection	Alphanumeric	
Burglary protection	Alphanumeric	
Motorized, electronic opening	Boolean	
Optional properties		
Fabrication year	numeric	
Fitting types	alphanumerical	hinges, handles, lever handles
Sensors	alphanumeric	

Table 21 Necessary and optional reuse properties: Lamps

Mandatory properties		**Optional properties**	
Property	*Data format*	*Property*	*Data format*
component name	alphanumeric	Fabrication year	numeric
Component types	alphanumerical	Operating Voltage	numeric
height	numeric	Illuminant type	alphanumeric
depth	numeric	Transformer necessary	boolean
width	numeric	Operation mode	alphanumeric
material core (frame)	alphanumeric	Power per Lamp	numeric
material surface (frame)	Alphanumeric	Protection class	numeric
quantity	numeric		
unit	alphanumeric		
condition	alphanumeric		

Component distinction

During the on-site inpection, differentiation took place according to the visual distinguishing characteristics in Figure.

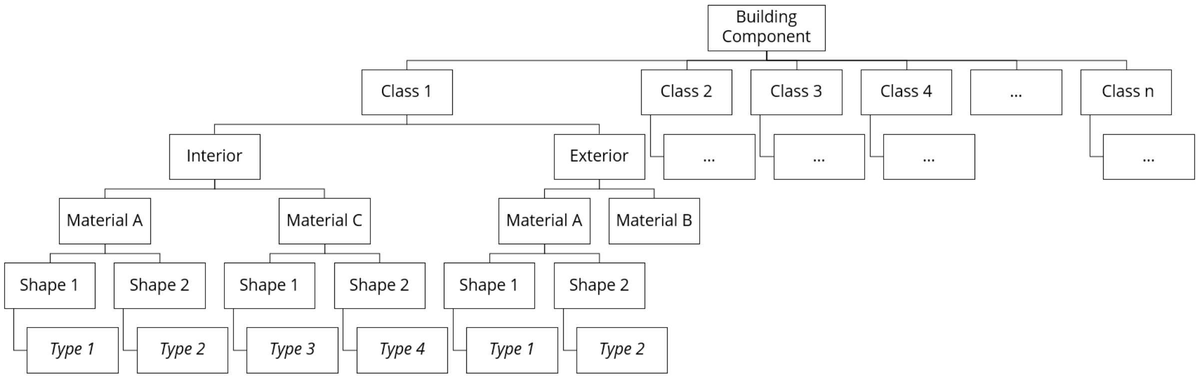

Figure 40 Component differentiation in in-site inspection (image by author)

The different classes of components are further divided into different types of components. A type differs in the following characteristics: interior or exterior component, component material, component shape. The definition of the type distinction is important for planning the annotation because the examples must be meaningful and differentiable. Unlike rule-based learning, in which the differentiation occurs according to rules pertaining to specified features, in ML, this differentiation rule learns itself based on the features identified by the model.

4.2. COMPONENT IDENTIFICATION USING MACHINE LEARNING

The thesis has found that the circular economy is far from being established in the AEC sector due to diverse barriers. Urban mining requires several steps, such as the inspection of the building before the demolition, detecting reusable components, taking inventory, planning of deconstruction etc. Furthermore, a certain level of expertise and time are required, which implies additional costs compared to a conventional demolition. Still, as established in the previous chapter, the existing reuse practice largely relies on analog workflows. Significant disadvantages of the analog urban mining workflow are the error-proneness in the data collection, evaluation, and documentation and the temporal expenditure of the onsite assessments.

The premise of this thesis is to contribute to the acceleration of the established urban mining practice by automatizing the onsite assessment (steps (4) and (5)) including the component detection and classification using machine learning technologies. Therefore, in this chapter firstly the scope of the machine learning algorithm and special requirements resulting from the use of 360° images are elaborated. Secondly, techniques to identify components are analyzed and subsequently, a selection of machine learning algorithms based on the performance estimation takes place.

4.2.1. SCOPE

The objective of this research is to facilitate the reuse of components by utilizing Machine Learning techniques and 360° images. Component reuse is reliant on several factors and properties, including numerical and alpha-numeric characteristics, as discussed in the previous chapter. Machine Learning can be optimally employed to predict the potential for component reuse and independently describe or categorize the components. An ideal model should not only classify components into pre-existing categories but also utilize unsupervised learning models to group them based on their component type, material, and size. The chapter 6.5 Future Research contains a detailed explanation of this approach and its potential intersection with other digital technologies, such as RMMs, material passports, and BIM, and should be considered as a future research opportunity. However, due to time and resource limitations this paper does not address this ideal solution. The scope of this research is to demonstrate that the combination of Machine Learning applications and 360° images, commonly utilized in inventory assessments, can enable, and expedite the reuse of certain components by largely automating the recording or inventory process and reducing the amount of necessary human interaction.

Therefore, the ML application should solve the following tasks:

1) Identification of various components in 360° imaging, with a focus on selecting reusable components
2) Categorization of the components into different types.
3) Listing of elements in each type as material passports, including an image of each component. The output can be in PDF or Excel format.

Drawing on chapter 2.3.2 The Task T this type of computer vision task corresponds to object class recognition. As established above object class detection focuses on recognizing (always unseen before) instances of some pre-defined categories (Zhang et al., 2013, p. 2), which in this thesis translates to identifying components belonging to the defined reusable component types (windows, doors, sanitary, lightning and heating).

The identification of reusable components in 360° images as in task (1) relates to the object classification task, which *"determines whether or not any instance of the categories of interest is present in a given image"* (Zhang et al., 2013, p. 4). As in scope (2) multiple classes (doors, windows, sanitary, lightning and heating) are of interest, the task is a multi-class detection task (Salakhutdinov et al., 2011), by which all instances (components) of these predefined categories are detected (Zhang et al., 2013, p. 5).

In this thesis, the terms "class" or "category" refer to a group of objects (component types) sharing common semantic features, such as "door" or "window". On the other hand, "object" or "instance" refers to a specific individual (component) within a class. It should be noted that these pairs of terms are used interchangeably. (Zhang et al., 2013, p. 4)

4.2.2. ANALYSIS OF TECHNIQUES FOR IDENTIFYING COMPONENTS

In this section, techniques to identify components are analyzed and the model selection, i.e. the performance estimation of different models in order to choose the best one, is performed. The selected model is then trained in 5.2 Training and validated in 5.2.3 Validation to estimate its prediction error (Hastie et al., 2009, p. 222).

In the realm of generic object detection, the ultimate objective is to design a versatile algorithm that can achieve the two competing goals of high accuracy and high efficiency. High-quality detection entails precise localization and recognition of objects in images or video frames, which facilitates the differentiation of a wide range of object categories prevalent in the real world (i.e., high distinctiveness) and localization and recognition of object instances within the same category while considering intra-class appearance variations (i.e., high robustness). High efficiency demands that the entire detection process must operate in real-time while keeping memory and storage requirements within acceptable limits (Liu et al., 2018a, pp. 4–5). At present, convolutional neural networks (CNNs) are widely regarded as one of the most powerful tools in the field of computer vision (Su and Grauman, 2017, p. 1) and frameworks (region-based and unified) play a crucial role in reducing the computational cost. Region based (or two-stage) detectors implement the R-CNN architecture, which is subsequently followed by its variations including Fast R-CNN (Girshick, 2015), FasterR-CNN (He et al., 2017; Ren et al., 2015) and Mask R-CNN (He et al., 2017) (Li et al., 2023, p. 510). Among the one-stage frameworks, OverFeat (Sermanet et al., 2013), DetectorNet (Szegedy et al., 2014), You Only Look Once or Yolo (Redmon et al., 2016) and Single Shot Detector or SSD (Liu et al., 2015) are the most popular (Liu et al., 2018a, p. 13). However, state-of-the-art research mainly focuses on using conventional 2D images.

Conversely to 2D images, 360° images are interpreted as a sphere or spheroid around the camera viewpoint. As seen in 2.6 360° Imaging, *"360°images are usually represented in either equirectangular projection (ERP) or (multiple) perspective projections (PSP)"* (Zhao, P. et al., 2019, p. 1). *"Perspective projections offer less distortion, but require projecting a large number of candidate areas to cover"* (Zhao, P. et al., 2019, pp. 1–2) and are therefore less efficient. In this thesis the equirectangular projection of the images will be used as input.

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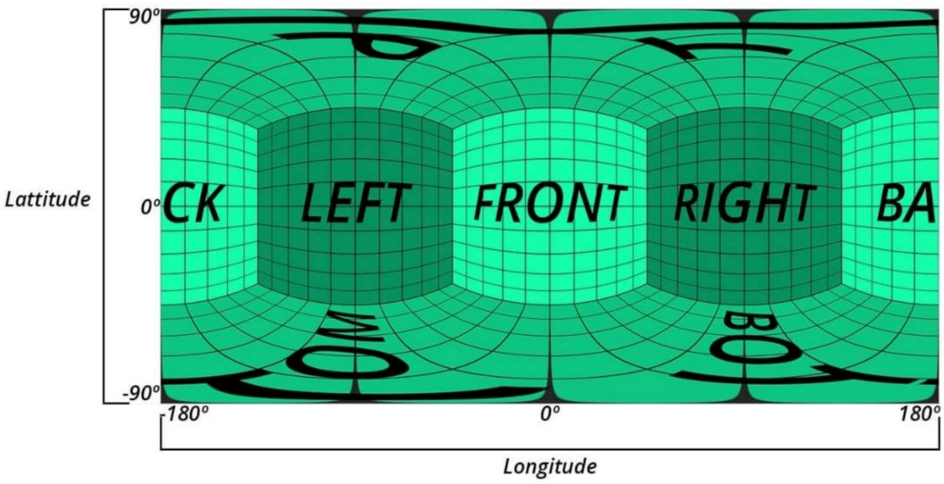

Figure 41: Equirectangular projection (Trek View, 2020)

“Although most object detection neural networks designed for the perspective images are applicable to 360° images in equirectangular projection (ERP) format” (Cao et al., 2022, p. 1), the *“conversion of 360° content to the projection plane introduces geometric distortion […], which results in inefficient feature extraction by the neural network. Moreover, the objects located at the boundary of the projection image appear incomplete”* (Li et al., 2023, p. 508). *“The distortions of objects vary with distance and viewpoint (see* Figure 42*) and show randomness to some extent”* (Fucheng Deng et al., 2017, p. 375). The lack of high-resolution images and a lack of annotated training data are other challenges in the object detection using equirectangular panorama images (Yang et al., 2018).

Figure 42 Example of equirectangular projection.
The distortion varies with distance of the object from the viewpoint. The doors in proximity to the image center (dark blue) appear more distorted than the door in the distance (light blue). (Bendiek Laranjo, 2023)

To overcome these challenges, two general approaches are distinguished in the application of CNNs for object detection in 360° images:

1) applying object detection models on the planar projection of a spherical image, or
2) repeatedly projecting the 360° image to tangent planes, (Su and Grauman, 2017, p. 2).

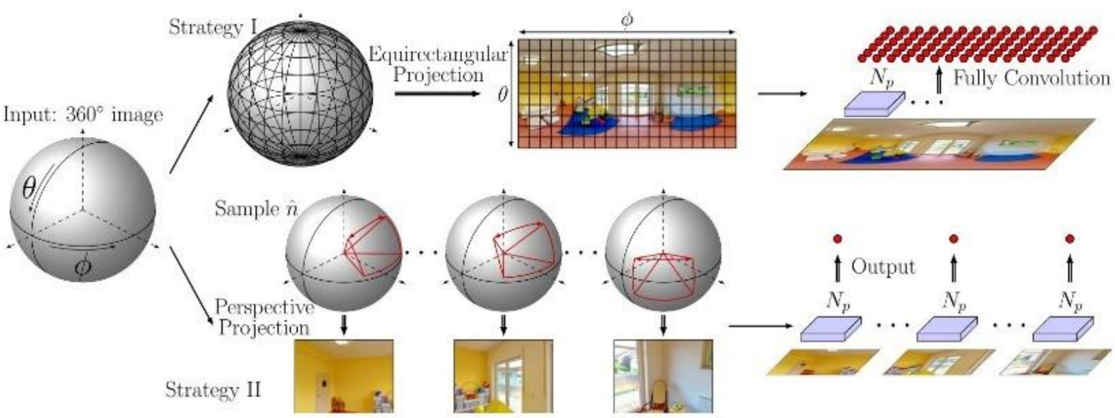

Figure 43 Approaches working with 360° images (Su and Grauman, 2017, p. 2)

The first approach involves the application of conventional object detection models on equirectangular images (Chou et al., 2020) or the optimization of the convolution layers using distortion-aware convolution modules, which can handle the geometric deformation during the feature extraction stage (Li et al., 2023, p. 511). Approaches so far proposed deformable convolution (DeformConv) to improve CNN feature extraction on panorama images (Dai et al., 2017). Hu et al. (2019) improved DeformConv addressing the issue of useless context regions interfering with feature extraction. Furthermore, Spherical CNN (Cohen et al., 2018) have been proposed for classification and geometric distortion encoding rotational invariance methods. Fernandez-Labrador et al. (2019) proposed equirectangular convolution (EquiConv) to eliminate geometric distortion under equirectangular projection, while orthographic convolution (OrthConv) is designed for orthographic projection (Li et al., 2023, p. 510). In addition, Coors et al. (2018) created the synthetic FlyingCars dataset by attaching rendered 3D car images to real-world omnidirectional images, and solved the distortion in ERP using spherical convolution applied to a vanilla SSD (Zhao, P. et al., 2019, p. 3). Most recently Li et al. (2023) proposed a novel two-stage detection network, RepF-Net, that utilizes multiple distortion-aware convolution modules to efficiently extract features and deal with geometric distortion in 360°content, developed to address the problem of incomplete objects at the boundary of projection images (Li et al., 2023, p. 508). This is only a list of popular distortion aware CNN and does not claim to be complete.

The second approach, on the other hand, works with spherical images without using ERP. This approach was pursued by Yang et al. (2018) who used a multi-projection variant of the YOLO detector (mp-YOLO) to handle the geometric deformation issue by using multiple stereographic projections. Based on that, Zhao et al. (2020, p. 12959) proposed Reprojection R-CNN (Rep R-CNN) *"by combining the advantages of both ERP and PSP, yielding efficient and accurate 360°object detection"* (Zhao et al., 2020, p. 12959). The Rep R-CNN detector has two stages: a spherical region proposal network (SphRPN) for efficiently proposing coarse detections on ERP, and a reprojection network (RepNet) for accurately refining the proposals based on PSPs (Zhao et al., 2020, p. 12962). The detector outperforms previous methods, including the multi-projection YOLO, by over 30% on mAP[5] with competitive speed (Zhao et al., 2020, p. 12959). Finally, the spherePHD detection model proposed by Lee et al. (2019) projects an omnidirectional image onto an icosahedral spherical polyhedron[6] and applies it to a CNN structure, resulting in a representation with significantly less irregularity compared to ERP and other representations (2019, p. 9175). Lastly, SPHCONV proposed by Su and Grauman (2017) is a hybrid form of the two approaches, in which a CNN is learned *"that processes a 360° image in its equirectangular projection (...) but mimics the "flat" filter responses that an existing network would produce on all*

5 mAP – mean average precision (see 0 Metrics)

6

tangent plane projections for the original spherical image (...)" (Su and Grauman, 2017, p. 2).

In Table 61 in Annex IV a compilation of these popular object detection models capable of processing equirectangular images was analyzed to determine the most suitable technique for enabling component reuse in the AEC sector. The models were gathered in research publications (Chou et al., 2020; Li et al., 2023; Liu et al., 2018a; Su and Grauman, 2017; Zhang et al., 2013; Zhao, Z. Q. et al., 2019) and conference outcomes, including the Conference on Computer Vision and Pattern Recognition (CVPR), International Conference on Computer Vision (ICCV), and European Conference on Computer Vision (ECCV), and then evaluated according to the criteria presented in Annex IV.

4.2.3. TECHNIQUE SELECTION

The final selection of the object detection model for training and validation was made for the following reasons: First, this thesis' aims to demonstrate the suitability of machine learning methods for detecting reusable components in the context of 360° images. Therefore, developing a proprietary model is beyond the scope, which limited the model selection to publicly available implementations. Second, it was logical to train a model for each of the two presented approaches, however, due to limited resources, it was not possible to annotate the dataset in both equirectangular projection and a spherical projection. However, this comparison is considered very important and offers the potential for future research topics (see 6.5 Future Research). As a result, for the sake of comparability and limited computational resources, a conventional one-stage detector, *YOLO*, was chosen. Different versions of this one-stage-detector have already been applied in the field of object detection in 360° images (see (Chou et al., 2020), (Yang et al., 2018)), as well as being frequently used as a benchmark model, for example in (Zhao, Z. Q. et al., 2019) and (Zhao et al., 2020). The model is briefly described below.

YOLO

"You Only Look Once" or YOLO is a "*unified, real-time object detection*" model proposed by Redmon et al. (2016). While SOTA detection models hitherto had repurposed classifiers to perform detection, YOLO formulated object detection *"as a single regression problem, straight from image pixels to bounding box coordinates and class probabilities."* (Redmon et al., 2016, p. 779). It combines feature detection, bounding box and class probabilities prediction in a single neural network. Unlike other object detection models that are based on sliding window or region-proposal based techniques, YOLO uses features from the entire image to predict each bounding box and simultaneously predicts all bounding boxes for all classes. Therefore, the input image is divided into an $S \times S$ grid and the grid containing the center of an object is responsible for this object's detection. Each grid cell predicts B bounding boxes and their corresponding confidence values for object presence and accuracy. The confidence value should be zero, if no object exists in that cell, and otherwise correspond to the intersection over Union (IoU) between the predicted field and ground truth. The confidence is defined as:

$$Pr(object) * IOU_{pred}^{truth}. \qquad \textit{Equation 4-1}$$

For each grid cell, the model predicts C conditional class probabilities, $Pr(Class_i|Object)$, given that an object is present in that cell. Only one set of class probabilities is predicted per grid cell, independently of the number of bounding boxes B. In the test run the class-specific confidence score that encodes both the probability of a class's presence and the accuracy of the predicted box fitting the object, is calculated by multiplying the conditional class probabilities and the individual box confidence predictions (Redmon et al., 2016, p. 780):

$$Pr(Class_i|Object) * Pr(Object) * IOU_{pred}^{truth} = Pr(Class_i) * IOU_{pred}^{truth} \qquad \textit{Equation 4-2}$$

Yolo is implemented as convolutional neural network (see 2.4.3 Convolutional Neural Networks) in which the *„initial convolutional layers [...] extract features from the image while the fully connected layers predict the output probabilities and coordinates“* (Redmon et al., 2016, p. 780).

The network architecture consists of 24 convolutional layers followed by 2 fully connected layers. It is inspired by GoogLeNet, but uses 1×1 reduction layers followed by 3×3 convolutional layers instead of the inception modules. The network outputs a 7 × 7 × 30 tensor of predictions. (Redmon et al., 2016, pp. 780–781) The network is shown in Figure 44.

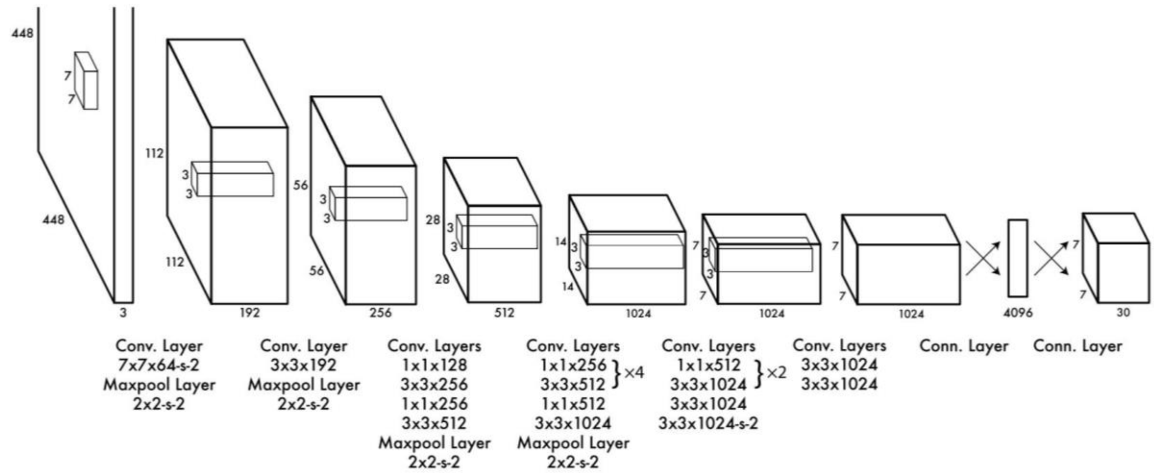

Figure 44: The YOLO detection model architecture (Redmon et al., 2016, p. 781)

5 MACHINE LEARNING PIPELINE

After the problem framing in 4.2.1 Scope and selecting an appropriate model in 4.2.3 Technique selection this chapter will elaborate on the machine learning pipeline for the task of identifying reusable components. A ML pipeline refers to a sequence of steps or formalized processes that are intended to standardize machine learning projects (Hapke and Nelson, 2020).

In this thesis, the pipeline comprises three main processes, including data acquisition and preparation (section 5.1 Data), training and validation techniques (5.2 Training and Validation), as well as the final testing and evaluation methods (5.3). It should be noted that the deployment of the validated model and its scaling (Hapke and Nelson, 2020) are beyond this thesis' scope.

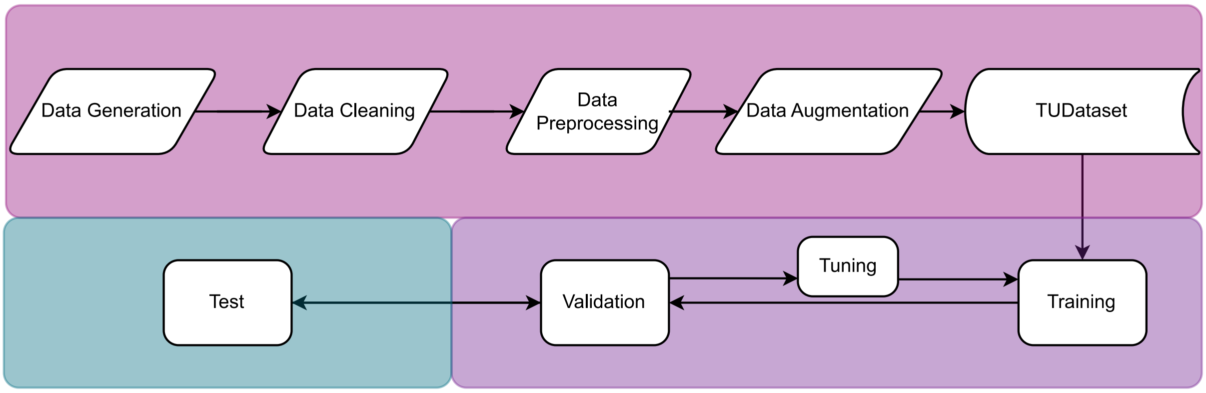

Figure 45 Machine Learning Pipeline (image by author)

5.1. DATA

Data is the foundation of any machine learning project. The model's usefulness and performance rely on the quality of the data used for training, validation, and analysis (Hapke and Nelson, 2020). This chapter focuses on the first step of the machine learning pipeline that comprises the dataset generation, image annotation, pre-processing, format conversion, and splitting into training, validation, and test sets.

In 5.1.1 appropriate datasets are considered and the necessity to generate a proprietary dataset is outlined. In 5.1.2 the image generation for the TUDataset is described, while the feature and category selection is conducted in 5.1.3 to guide the annotation process in 5.1.5. The collected data is then cleaned and normalized in 5.1.4 and augmented (5.1.6).

Finally, the dataset is split into training, validation, and testing sets for supervised learning approaches in 5.1.6 and converted to a suitable format. By following this process, a high-quality dataset can be prepared to train a machine learning model.

Table 22 Overview of the used software for data deployment

Steps	**Software**
Data generation	Openexperience Bauhelm
Preprocessing	Roboflow
Annotation	Roboflow
Training	PyCharm

5.1.1. DATASETS

Various publicly accessible datasets exist on the internet, catering to diverse visual tasks (i.e. categorization, detection, or segmentation), with different sources of images and annotations such as category names, bounding boxes, and pixel-level labels (Zhang et al., 2013, p. 38). Most popular datasets are: Pascal VOC (Everingham et al., 2010), ImageNet (Russakovsky et al., 2014), MS COCO (Lin et al., 2014), Places (Khosla et al., 2018), Open Images (Alina Kuznetsova et al., 2018). However, these datasets include exclusively conventional images that impose limitations on current computer vision algorithms by restricting the visual field to a narrow region. These restrictions are overcome by 360° images (also “omnidirectional” or “panoramic” images), that offer a comprehensive view of the scene. The popularity of 360° omnidirectional images has been on the rise (Cao et al., 2022; Chou et al., 2020; Feng et al., 2020; Zhang et al., 2022) due to their ability to capture more comprehensive scene information than traditional images. As a result, they are meeting the growing need for a wider field of vision in various settings, including both industry and daily life (Zhang et al., 2022, p. 1). In the construction industry, 360° images are gaining popularity in building documentation. With the growing amount of data, there is an increasing interest in computer vision to explore 360°visual recognition (Chou et al., 2020, p. 835). Therefore, several 360° datasets have recently been developed (Chou et al., 2020). Based on the existing 360° dataset compilations by Chou et al. (2020) and Xu et al. (2022) in Table 22 (p. 99) an updated list of existing datasets is presented.

“However existing equirectangular projection image datasets, including Sun360, PanoContext, SunCG, Stanford2D3D, and Structured3D, all lack standard object detection annotations”(Li et al., 2023, p. 516). The 360-Indoor Dataset stands out because of its similar domain and object detection scope. It was released in 2020 by Chou et al. (2020) and was the first and largest object detection and classification dataset available. It comprises 3,000 equirectangular indoor images and 90,000 annotations for Bounding FoVs (BFoVs) across 37 categories in its present version (Chou et al., 2020).

Table 23 Existing 360° datasets in 2D domain to date, based on (Xu et al., 2022) and (Chou et al., 2020)

Datasets	360° Data type	Domain	Purpose	#images/ videos	# categ.	# boxes	Annotation	
360-Indoor	images	indoor scenes	Object detection	3000	37	89148	Bounding Field of View	(Chou et al., 2020)
Matter-port3D	images	Indoor scenes of 90 buildings	Object Segmenta-tion	10.800	40	50811	Instance-level segmentation Masks	(Chang et al., 2017)
SUN360	images	Indoor and outdoor scenes	Not specified	67583	80	-	not annotated	(J. Xiao et al., 2012)
Stanford 2D-3D-S	images	Indoor spaces (13 room types)	Seg-mentation	1413	13	5614	Instance-level Segmentation Masks	(Armeni et al., 2017)
What's in my room?	Images	indoor scenes	Seg-mentation	666	14		Segmentation Masks	(Guer-rero-Viu et al., 2020)
Deng et al.	Images	Indoor scenes	Object detection	2000	8		Bounding Boxes	(Fucheng Deng et al., 2017)
Pano2Vid	Videos	Outdoor ac-tivities	Automatic Cinematog-raphy	86	-	-	not annotated	(Yu-Chuan Su et al., 2016)
Sports-360	360° Vid-eos	Sports	Visual Pilot, Object de-tection				Viewing Angles	(Hu et al., 2017)
YouTube/ Vimeo	360° , normal field-of-view (NFOV) vid-eos	Wed-ding/Music Videos	Highlight detection	115 (360° vid-eos)	-	-	not annotated	(Yu et al., 2018)
Narrated-360	Videos	House/Tour Guiding	Visual Grounding	864	-	-	Bounding Box	(Chou et al., 2017)
Wild-360	Videos	Nature and Wildlife	Saliency De-tection	85	-	-	Saliency Map	(Cheng et al., 2018)
ERA	images (video frames)	Dynamic activities	Object detection	903	10	7199	Bounding Field of View	(Yang et al., 2018)
Flying Cars	Images	Synthesis Cars (3D car models)	Object detection	-	1	6000	Bounding Field of View	(Coors et al., 2018)
OSV	Images	Streets scenes (Ja-pan)	Object detection	600	5	5058	Bounding Box	(Yu and Ji, 2019)
Pandora	360° Im-ages	Indoor scenes	Object detection	3000	47	94353	Rotated Bounding Field of View(RBFoV)	(Xu et al., 2022)

Although the 360-Indoor represents a *"new benchmark for visual object detection and class recognition in 360°indoor images"* (Chou et al., 2020, p. 834), it was decided to generate proprietary data for the following reasons: The dataset was generated using public images in the databases Flickr[7], Kuula[8], and the dataset "Narrated 360° videos" (Chou et al., 2017). As a result, the set contains a large number of images of a wide variety of buildings, but these images only very poorly describe the respective building. It is often recognizable from the interior design that several images must come from one (public) building, but no conclusion can be drawn about the rest of the premises.

This thesis aims to enable the recognition of building components for reuse by automatic recognition using ML. The following working hypotheses are used: Urban mining projects usually include one or more buildings to be considered in their entirety. Furthermore, within a building, it can be assumed that a selection of different designs (types) of a building component is frequently repeated. For example, in practice, uniform window types are often found per façade and floor: for instance, in residential buildings up to about the 1950s, window fronts are often found on the ground floor, and the largest windows are pm 1st floor (the "belle étage") than on the floors above. Smaller window sizes face the courtyard that remain constant throughout the building were usually installed. With 37 labels the 360-Indoor dataset currently has "*the largest category number" (Chou et al., 2020, p. 834),* but lacks the intra-class variation required for reuse: for the next-life considerations the format, materiality and the design of the components are required information and a distinction between outdoor and indoor components is useful (see 5.1.3 Category Selection).

Finally, for good generalization it is crucial that the training data is representative of the new cases that will be generalized to (Géron, 2023, p. 25). Hence, a dataset is needed that documents the entire building, , in which the different types of components within a class are frequently repeated. For these reasons, the need to create a separate dataset was seen and the TUDataset was generated as described below.

[7] https://flickr.com/

[8] https://kuula.co/

5.1.2. DATA GENERATION: TUDATASET

Spherical object detection datasets can be generated using various methods (Zhao et al., 2021). The first method, used by Su and Grauman (2017) and Zhao, P. et al. (2019), is the transformation of planar datasets to panoramic ones, e.g. by randomly cropping objects with backgrounds of varying sizes from images, and subsequently projecting these cropped images onto arbitrary points on a sphere (Zhao et al., 2020, pp. 12963–12964). Another approach is to composite real-world background images with rendered or segmented images (Coors et al., 2018; Zhao et al., 2020), as seen in the FlyingCars dataset, which integrates real-world panoramic images captured by an omnidirectional 360° action camera with computer-generated 3D car models (Coors et al., 2018, p. 537). Thirdly, synthetic images with pixel-level annotations can also be generated from virtual worlds as in the SYNTHIA dataset (Ros et al., 2016). Finally, some methods involve the generation of data using specialized cameras or profiting of the increasing prevalence of omnidirectional sensors in drones, robots, and autonomous cars (Cohen et al., 2018). These images are then manually annotated in spherical images, as opted by Zhang et al. (2022) or, more frequently, in the equirectangular projection of the image.

In this thesis the data was generated from scratch using the specialized cameras. Specifically, an OpenExperience 360° camera helmet (as seen in Figure 46) was used to capture real-life images.

Figure 46: DIGIBAU 360° helmet camera (DIGIBAU 360°-Baudokumentation, 2023)

Two 180-degree cameras are installed in the helmet, whose individual images are subsequently stitched together to one spherical 360° image. The ERP of the images have a resolution of 7000 x 3500 pixels, a horizontal and vertical resolution of 96 dpi, and a bit depth of 24.

To ensure the suitability of the captured images for recognizing reusable building components, two modern buildings (Nürnberger Ei, built in 1996, and House 116 in August-Bebel-Strasse 30, built in 1970 and renovated in 2013), as well as three buildings of reform architecture from the early 20th century (Beyer-Bau, built in 1913; Fritz-Foerster-Bau, built in 1926; and Georg-Schumann-Bau, built in 1906) were selected. Due to the similar architecture and authorship an overlap in the component selection for the reform buildings was anticipated. Moreover, the dataset will be made publicly available in the future, making it advantageous to record images in public buildings. A total of 1112 images were captured. The image generation protocol is found in Table 24.

Table 24 Data generation protocol

Generation Date	**Building**	**Location**	**Construction Year**	**Images**
30.03.2023	Fritz-Foerster-Bau	Mommsenstraße 6, 1069 Dresden	1926/2022	280
30.03.2023	Nürnberger Ei	Nürnberger Straße 31a, 01187 Dresden	1996	37
31.03.2023	Georg-Schumann-Bau	Münchner Platz 3, 01187 Dresden	1906	369
31.03.2023	Haus 116	August-Bebel-Straße 30, 01219 Dresden	1970/2013	159
14.04.2023	Beyer-Bau	George-Bähr-Straße 1, 01069 Dresden	1913	277
				1122

Some of the main challenges for machine learning are related to the data and accordingly to the quality of the dataset. A dataset should consider the following factors: size of the dataset, representativeness, relevance, date (image) quality (Géron, 2023, pp. 23–27) and variance.

The importance of quantity was shown in Banko and Brill (2001)'s renowned experiment, in which different learning methods, even those that were relatively simple, showed nearly equal proficiency in solving a challenging task of natural language disambiguation when provided with sufficient data (Banko and Brill, 2001, pp. 27–28).

With 1112 unaltered images the TUDataset can be considered a mid-sized dataset (before data augmentation), but due to the representativeness of the data (during data-cleaning only images with at least one relevant component were included), the quantity is considered sufficient for the task at hand. Furthermore, the relevance of training data can be defined as the extent to which it aligns with the data that the model is likely to encounter in the production phase (Witt, 2023). The model will be used prior to demolition of a building or to inventory the building for planning its conversion or continued use. Therefore, the selected locations for generating the dataset can be considered meaningful for the subsequent use of this model. Finally, the dataset offers a vast range of object categories and intra-class variations, which can be explained by the imaging conditions. First, the data was captured at different times of the day and under varying weather conditions, resulting in different lighting and shading conditions. Furthermore, the images were taken without a fixed object distance, often capturing the same room from different positions and from a person's viewpoint, so that a variance in the object appearance, scale and occlusion is generated. Also, the use of a helmet camera instead of a tripod camera leads to the fact that the images have different resolutions and components are displayed both high-resolution and slightly blurred. Lastly, the choice of the buildings leads to the representation of different equipment and corresponding image clutter: The refurbishment of the Fritz-Förster-Bau has just been completed, so the premises have only recently been occupied and are partly still empty. The Beyer Building is in a not-yet-completely-rehabilitated state, which could also correspond to the condition after a partial gutting and thus an end-of-life scenario. The Nürnberger Ei, as well as the Schumann-Bau, contain offices and corresponding equipment.

In summary, the diverse set of images captured under different conditions allows for better generalization of the model, improving its performance on real-world scenarios where object appearance and environmental factors vary significantly. The resulting dataset is named TUDataset after the location of the image generation and the author's affiliation.

Modern buildings and their locations included in the TUDataset

Figure 47: View of August-Bebel-Straße 30 after the renovation in 2012 (Meyer, 2023)

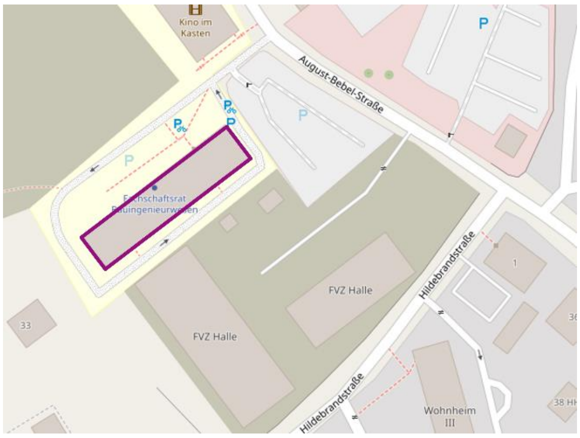

Figure 48: Haus 116, August-Bebel-Straße 30, 01219 Dresden, Germany, Screenshot of Map Area, (OpenStreetMap, 2023), OdbLv1.0

Figure 49: View of the Nurnberger Ei. (Terfloth, 2023), (CC-SA-3.0)

Figure 50: Institute of Construction Informatics, Nürnberger Str. 31a, 01187 Dresden, Germany, Screenshot of Map Area, (OpenStreetMap, 2023), OdbLv1.0

Reform architecture buildings and their location used in the TUDataset

Figure 51: View of the Georg-Schumann-Bau. (Blobelt, 2021), (CC BY-SA 4.0)

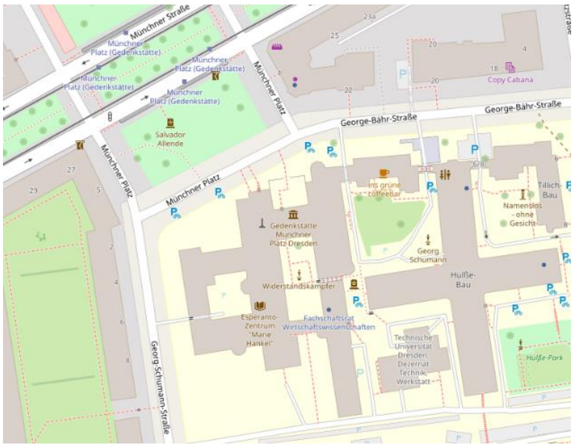

Figure 52: Georg-Schumann-Bau, Münchner Platz 3, 01187 Dresden, Germany. Screenshot of Map Area, (OpenStreetMap, 2023), OdbLv1.0

Figure 53: View of the Beyer Bau after facade renovation in 2021, (CC BY-SA 4.0) (Ponna, 2021)

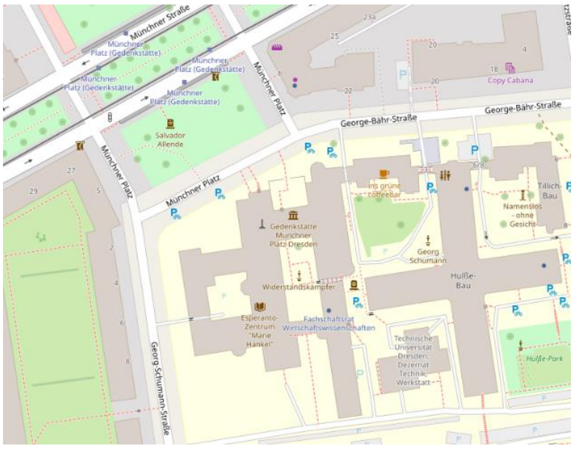
Münchner Straße
Münchner Platz
George-Bähr-Straße
Copy Cabana
Salvador Allende
Gedenkstätte Münchner Platz Dresden
Widerstandskämpfer
Georg Schumann
Hülße-Bau
Esperanto-Zentrum "Marie Hankel"
Fachschaftsrat Wirtschaftswissenschaften
Technische Universität Dresden Dezernat Technik Werkstatt
Hülße-Park
Georg-Schumann-Straße

Figure 54 Beyer-Bau, George-Bähr-Straße 1, 01069 Dresden, Germany. Screenshot of Map Area, (OpenStreetMap, 2023), OdbLv1.0

Figure 55: View of the Fritz-Foerster-Bau after ther renovation 2023.(Gebhardt, 2023), (CC BY-SA 4.0)

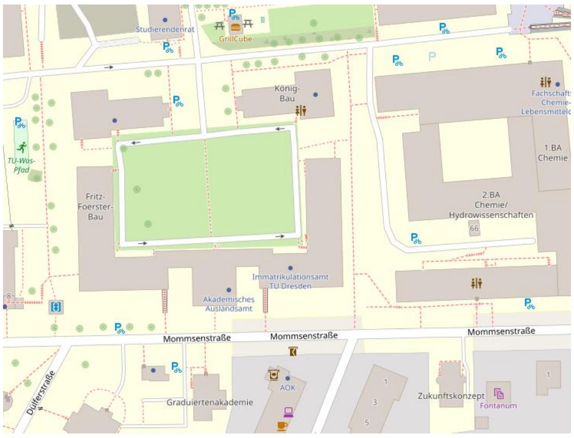

Figure 56 Fritz-Foerster-Bau, Mommsenstraße 6, 01069 Dresden, Germany. Screenshot of Map Area, (OpenStreetMap, 2023), OdbLv1.0

5.1.3. CATEGORY SELECTION

One important step in the data set preparation is to consider how the objects should be recognized and categorized to match the scope: This thesis aims at enabling component reuse by accelerating the inventory of reusable components in the end-of-use phase.

Therefore, a higher granularity of the reuse component categories "windows, doors, sanitary objects, electrical installation" is necessary so that the components can be inventoried according to the planning steps from section 724.1.2 How to reuse. To ensure consistency and minimize subsequent editing of the output, it is recommended to refer to common categories.

Standardization would be possible using established ontologies as well as the reference to standards. However, since this thesis is considered a first approach but not the ideal solution, in which a direct link to digital planning is aimed through the 3D reconstruction of components (see 6.5 Future Research), the reference to standards is preferred for simple application of the approach in practice. Therefore, in this thesis the German AEC sector's building cost structure published by the national standard DIN 276:2018-12 (Deutsches Institut für Normung e.V., 2018), hereafter simplified as DIN276, was used to uniform the process. Categorization by cost group will not only standardize the work in different projects by reference to a public standard, it will also provide the operational basis for rapid cost determination for selective deconstruction. Thus, the first step was to determine the cost groups for the component selection (windows, doors, plumbing, lights and heating). It should be noted that windows and doors are sorted into different groups depending on their installation location, as seen in Figure 57.

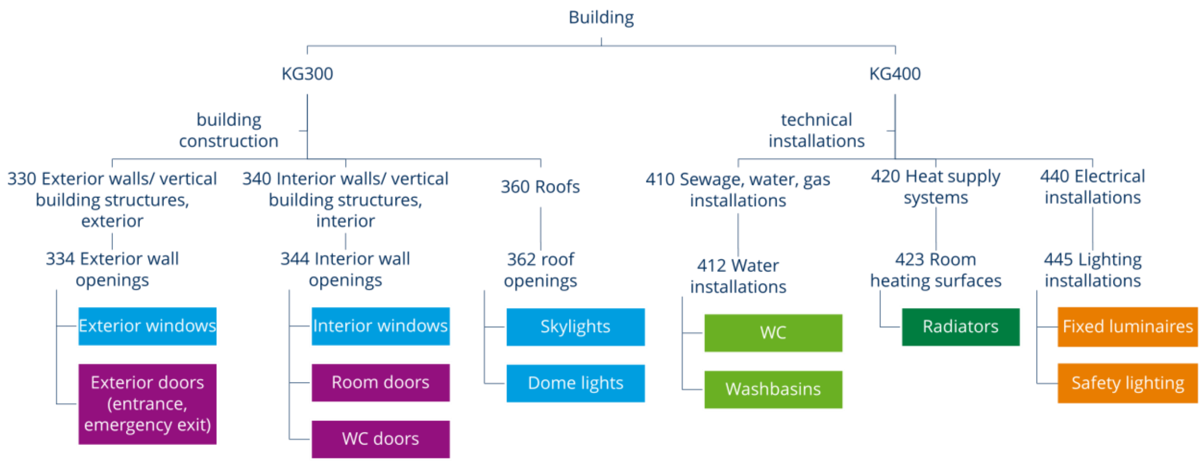

Figure 57 Reuse components sorted by cost groups according to DIN276 (Deutsches Institut für Normung e.V., 2018) :windows (blue); doors (purple); sanitary (green); heating (dark green); lights (orange);

Hence, it is useful to establish the component types as super-categories and the different cost groups as component categories.

5.1.4. DATA CLEANING

In the context of data preprocessing for machine learning applications, the following steps are often undertaken:

(i) removal or correction of outliers in the dataset;
(ii) substitution of missing values with appropriate strategies, such as zero, mean or median imputation or removal of the affected rows or columns;
(iii) optional feature selection process to remove redundant or irrelevant attributes;
(iv) feature engineering operations including discretization of continuous features, decomposition of categorical, date/time features, addition of potential feature transformations, and aggregation of features into new ones; and
(v) feature scaling through standardization or normalization techniques to ensure uniformity and comparability across features. (Géron, 2023, p. 757)

However, in object detection, images or videos are used as inputs, and the features are extracted from the information in the pixels. The YOLO (You Only Look Once) model employs a feature extraction method that does not require the prior definition and cleaning of features. Therefore, the data cleaning was limited to elimination of duplicates, exclusion of low-quality images and blurred images.

5.1.5. ANNOTATION

In supervised learning methods, like YOLO, "*the example contains a label or target as well as a collection of features"* (Goodfellow et al., 2016, p. 105). The process in which the label is generated to mark the features in the training example (image) is called *annotation*. In computer vision, the most commonly used type of annotation are bounding boxes (Pokhrel, 2020) that specify the object's class and its localization in the image. In two-dimensional scenarios, an object's spatial position and size are typically determined using an axis-aligned rectangle (x, y, w, h) that tightly encompasses the object, where (x, y) denotes the center point of the rectangle, and (w, h) represents the rectangle's width and height, respectively (Zhao et al., 2021, p. 4).

However, in the field of object detection in equirectangular images, no annotation approach has yet become completely accepted and further annotation types have derived from the common rectangular bounding boxes: Yang et al. (2018) used the *Bounding Field of View (BFoV)* or "*spherical rectangle"* (Xu et al., 2022, p. 239) annotation to ensure the consistent annotation for objects in equirectangular panorama images. The projection of panoramas can change an object's appearance depending on its spatial location, making it necessary to select a "canonical pose" (field of view) where bounding box coordinates are valid and have a box-like shape (see Figure 58: Example of a spherical images annotation: (a) Bounding Field Annotation and (b) a bounding box annotation, image by (Yang et al., 2018, p. 2)). In contrast to conventional bounding boxes represented by top-left and bottom-right corners, the ground truth annotations include: object label l_i, the bounding box center as angular coordinates ϕ_i, λ_i, and the bounding box angular dimensions $\Delta\phi_i, \Delta\lambda_i$. (Yang et al., 2018)

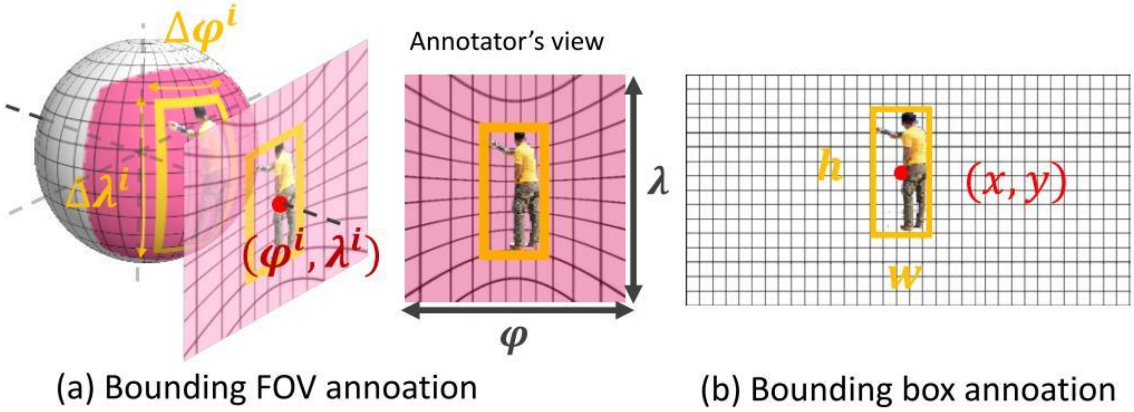

Figure 58: Example of a spherical images annotation: (a) Bounding Field Annotation and (b) a bounding box annotation, image by (Yang et al., 2018, p. 2)

Another type of annotation is the *Rotated Bounding Field of View (RBFoV)* introduced by Xu et al. (2022), which is characterized by five parameters: $\theta, \varphi, \alpha, \beta$, and γ. Here, θ and φ correspond to the longitude and latitude coordinates of the object center, while α and β represent the object's occupation angles in the up-down and left-right fields of view, respectively. Finally, γ denotes the angle of rotation (positive for clockwise and negative for counterclockwise) of the tangent plane of the RBFoV along the OM axis, where M is the tangent point (θ, φ) (Xu et al., 2022, p. 240).

Despite BFoVs and RBFoVs being "unbiased" (Xu et al., 2022, p. 239), in this thesis the common rectangular bounding box approach was chosen. This is because custom annotation tools must be used for other spherical annotations, as in (Xu et al., 2022) and (Chou et al., 2020). Furthermore, the spherical annotations need a prior conversion to the target format of the chosen model. According to the YOLO annotation format, the bounding box contains five predictions: x, y, w, h, and confidence. The (x, y) coordinates represent the centroid of the box in relation to the grid cell limits. The width and height are calculated in relation to the entire image. Finally, the IOU between the projected box and any ground truth box is represented by the confidence prediction. (Redmon et al., 2016, p. 780)

The annotation of the TUDataset was conducted in Roboflow[9], which is an online tool that offers various functionalities such as annotating images, converting annotation formats, preprocessing images, and augmenting images (Roboflow, 2023b), and resulted in 136 reuse component classes. The class diagram can be seen in

[9]https://roboflow.com/

Table 25 Classlabels used in the TUDataset in costgroup "Building Construction"

KG300					
Building Construction					
330 Exterior walls/ vertical building structures, exterior		340 Interior walls/ vertical building structures, interior			
334 Exterior wall openings		344 Interior wall openings			
Exterior windows	Exterior doors	Interior windows	Interior doors		
'window-exterior-bulleye1'	*door-exterior-entrance1'*	*'window-interior-type1'*	*'door-indoor-type1'*	*'door-indoor-glassdoor1'*	*'door-interior-emergency'*
'window-exterior-bulleye2'	*'door-exterior-entrance2'*	*'window-interior-type2'*	*'door-indoor-type2'*	*'door-indoor-glassdoor2'*	
'window-exterior-type1'	*'door-exterior-entrance3'*	*'window-interior-type3'*	*'door-indoor-type3'*	*'door-indoor-glassdoor3'*	
'window-exterior-type2'	*'door-exterior-entrance4'*	*'window-interior-type4'*	*'door-indoor-type4'*	*'door-indoor-glassdoor4'*	
'window-exterior-type3'	*'door-exterior-entrance5'*	*'window-interior-type5'*	*'door-interior-type5'*	*'door-indoor-glassdoor5'*	
'window-exterior-type4'	*'door-exterior-entrance6'*	*'window-interior-type6'*	*'door-interior-type6'*	*'door-indoor-glassdoor6'*	
...	*'door-exterior-entrance7'*	*'window-interior-type7'*	*'door-interior-type7'*	....	
'window-exterior-type59'	*'door-exterior-entrance8'*	*'window-interior-type8'*	*'door-interior-type8'*	*'door-indoor-glassdoor16'*	
'window-exterior-type60'	*'door-exterior-entrance9'*	*'window-interior-type9'*	...	*'door-indoor-glassfacade'*	
'window-exterior-type61'		*'window-interior-type10'*	*'door-interior-type24'*	*'door-indoor-glassdoor11'*	

Table 26 Classlabels used in the TUDataset in costgroup "Technical Installations"

<table>
<tr><td colspan="7">KG400</td></tr>
<tr><td colspan="7">Technical Installations</td></tr>
<tr><td colspan="3">410 Sewage, water, gas installations</td><td>420 Heat supply systems</td><td colspan="3">440 Electrical installations</td></tr>
<tr><td colspan="3">412 Water installations</td><td>423 Room heating surfaces</td><td colspan="3">445 Lighting installations</td></tr>
<tr><td>Toilet</td><td>Sink</td><td>Pissoir</td><td>Radiators</td><td colspan="2">Fixed lights</td><td>Safety Lighting</td></tr>
<tr><td rowspan="3">‘toilet’</td><td rowspan="3">‘sink’</td><td rowspan="3">‘pissoir’</td><td rowspan="3">‘radiator’
'radiator-vertical'</td><td>Wall</td><td>Ceiling</td><td>Emeergency</td></tr>
<tr><td>Wall</td><td>Ceiling</td><td>Wall</td></tr>
<tr><td>'light-fixed-wall'
'light-fixed-wall-dot'</td><td>'light-fixed-ceiling-LED'
'light-fixed-ceiling-dot'
'light-fixed-ceiling-luminaire'
‘light-fixed-ceiling-pendant’</td><td>'light-emergency'</td></tr>
</table>

5.1.6. SET PARTITION

After annotating the data, the next step is to split the dataset into training, validation, and test subsets. There are two distinct objectives in model analysis – model selection and model assessment – and in a data rich situation, the most effective approach is to randomly divide the dataset into a training set, validation set, and test set. The test-set is used for fitting the models, while the validation set is for estimating prediction error for model selection and test set is for assessing the generalization error of the final model configuration. The test set is kept reserved and not reused, as doing so can result in a substantial underestimation of the true test error. (Hastie et al., 2009, p. 222). The TUDataset was divided into 70% training (792 images), 20% validation (226 images) and 10% testing (116 images).

5.1.7. PREPROCESSING

The next step includes the application of preprocessing techniques to the training, validation, and testing sets to ensure that the machine learning model learns and infers based on consistent image properties. In computer vision, inference refers to the process of generating predictions (Roboflow, 2023a). The preprocessing steps suggested by Ultralytics include the Auto-Orientation and the size stretching to 640x640 pixels (Jocher, 2023a).

The auto-orient feature removes the EXIF (Exchangeable Image File Formal) data from images to ensure that they are displayed in the same manner as they are stored on the disk. The EXIF data contains metadata such as information on the orientation of an image, which applications utilize to present the image in a designated orientation, even if the stored orientation differs. (Roboflow, 2023a) Furthermore, YOLO relies on a CNN and requires a fixed size input, so that the default 640x640 size was chosen (Jocher, 2023a).

5.1.8. AUGMENTATION

The final step in the ML pipeline is the *data augmentation* or *training set expansion*, a the technique of artificially growing the training set (Géron, 2023, p. 465). Data augmentation creates multiple realistic versions of each training instance to artificially increase the training set size. This technique serves as a regularization method, reducing overfitting (see Training). To be effective, the augmented instances should be as realistic as possible and ideally be indistinguishable from non-augmented instances by the human eye. Realistic variations, such as shifting, rotating, and resizing images, improve the model's tolerance to position, orientation, and size changes. (Géron, 2023, p. 465)

In the preprocessing of the TUDataset several augmentation techniques were applied. The outputs per training sample were set to three, which means that for every image three altered images were created. Due to the particularity of the equirectangular projection training data augmentation techniques according to Zhao et al. (2021) were implemented: the images were flipped horizontally and sheared $\mp 15°$ horizontally and $\mp 15°$ vertically both on the image level and bounding box level (see Figure 59 and Figure 60-Figure 65). The data augmentation resulted in 2718 (3x792) images.

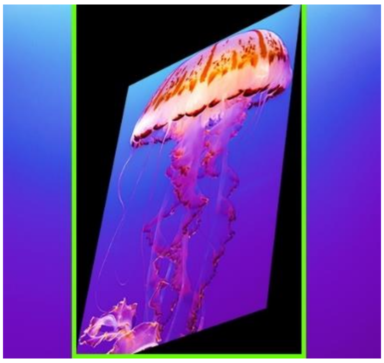

Figure 59: Data augmentation: horizontal and vertical bounding box shear (+-15°) (Roboflow, 2023c)

Figure 60: Data augmentation: Pre-processed image before flipping and image level shearing (0° horizontal, 0° vertical) (Roboflow, 2023c)

Figure 61: Data augmentation: Image horizontally flipped (Roboflow, 2023c)

Figure 62: Data augmentation: Image level shearing (+15° horizontally, +15° vertically) (Roboflow, 2023c)

Figure 63: Data augmentation: Image level shearing (+15° horizontally, -15° vertically) (Roboflow, 2023c)

Figure 64: Data augmentation: Image level shearing (-15° horizontally, +15° vertically) (Roboflow, 2023c)

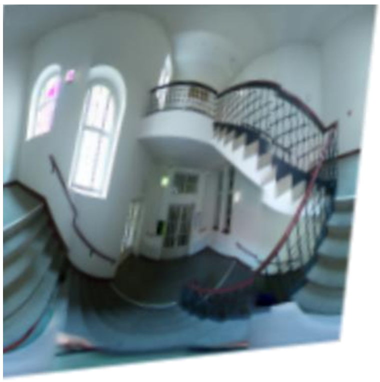

Figure 65: Data augmentation: Image level shearing (-15° horizontally, -15° vertically) (Roboflow, 2023c)

5.2. TRAINING AND VALIDATION

This chapter covers the training and validation of the YOLOv8 model. First, a choice is made between a pre-trained and an untrained model, and a model architecture is selected (5.2.1 Pre-Trained Model vs. Training from Scratch). Secondly, the training goal is formulated, and the used training arguments are explained in 5.2.2 Training Configuration. Next, the different model configurations will be compared and validated in 5.2.3 Validation. The performance of these models will be evaluated using various metrics, including accuracy, precision, recall, and F1 score, which will be briefly presented. Finally, in 5.2.4 the training strategy is explained based on the different training runs and a configuration is chosen out of the nine training configurations for the final test and evaluation on the previously unseen test set.

Furthermore, an iterative training and validation process is adopted as proposed by Géron (2023) in which the training configurations are tweaked based on the performance on an independent validation set. This is because of the risk of overfitting (see 5.2.3 Validation), wherein the model becomes excessively optimized for the test set and fails to generalize to novel data. Only after selecting a final configuration the model is evaluated on the test set. The approach is simplified in Figure 66.

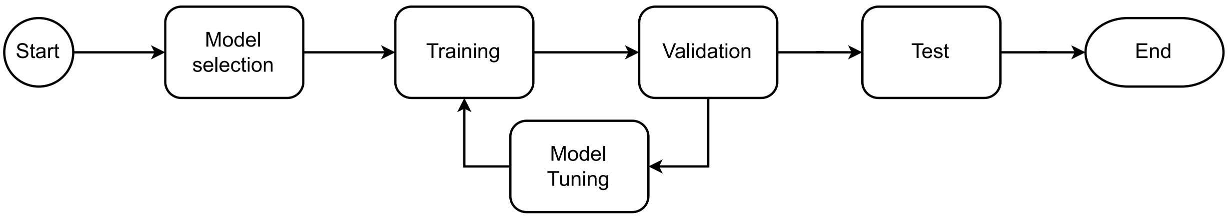

Figure 66 Iterative Training approach according to (Géron, 2023), (image by author)

It is noted that in this thesis "error" and "loss" are used interchangeably. Furthermore "validation error" and "test error" *"both refer to use of validation data to find the error or accuracy produced by the network during training"* (Smith, 2018, p. 2).

5.2.1. PRE-TRAINED MODEL VS. TRAINING FROM SCRATCH

Prior to training the model needs to be selected, choosing between a pre-trained and a simple model. There is a consensus among the AI community to exploit the benefits from transfer-learning by using pre-trained models (PTMs) as the backbone for downstream tasks rather than opting to train models from scratch (Han et al., 2021, p. 1). *Transfer learning* formalizes a two-phase learning framework: a pre-training phase to capture knowledge from one or more source tasks, and a fine-tuning stage to transfer the captured knowledge to target tasks. By fine-tuning PTMs with a small amount of task-specific data, they can perform well on downstream tasks, making them a feasible solution for the challenge of data scarcity. (Han et al., 2021, p. 2)

Accordingly, a YOLOv8 model pre-trained on the COCO dataset (Lin et al., 2014) was selected to target the object detection task with limited manually annotated data, namely the detection of reusable components in the TUDataset. Ultralytics, the YOLO developing company, offers various pre-trained YOLOv8 models that differ in their architecture and size (see Table 27). YOLOv8n has the smallest number of layers and parameters, making it the fastest and most lightweight model, but also potentially less accurate. YOLOv8s-YOLOv8l have increasingly more layers and parameters, thus decreasing in speed and increasing potential accuracy. Finally, YOLOv8x has the largest number of layers and parameters, making it the slowest but potentially the most accurate model. In general, larger models tend to perform better but are slower and require more resources to train and run. The selection process was constrained by the GPU capacity and ultimately resulted in the choice of Yolov8s.

Table 27 YOLOv8 pre-trained models as released by Ultralytics

Model	**Size**	**mAP^{val}**	**Speed CPU ONNX**	**Speed A100 TensorRT**	**params**	**FLOPs**
	[pixels]	*50-95*	*[ms]*	*[ms]*	*(x10^6)*	*(x10^9)*
YOLOv8n (nano)	640	37.3	80.4	0.99	3.2	8.7
YOLOv8s (small)	640	44.9	128.4	1.20	11.2	28.6
YOLOv8m (medium)	640	50.2	234.7	1.83	25.9	78.9
YOLOv8l (large)	640	52.9	375.2	2.39	43.7	165.2
YOLOv8x (extra large)	640	53.9	479.1	3.53	68.2	257.8

In the above table the columns express the following characteristics:

size	*input image size in pixels that the YOLOv8 models were trained and evaluated on.*
mAP	*mean average precision, metric to evaluate the object detection precision (see more in Metrics).*
Speed	*refers to the inference speed, the amount of time it takes for the model to process one input image and produce an output, when running on a CPU using the ONNX runtime and A100 GPU with TensorRT optimization.*
Params	*Number of parameters (weights and bias) in Millions*
FLOPs	*Number of floating point of operations in Billions; describes the computation complexity (Ma et al., 2021, p. 7)*

5.2.2. TRAINING CONFIGURATION

Training is the process of optimizing a machine learning model by reducing the error measure on a training set, called training error. The goal of training is not just to minimize the error on the training set, but also to achieve low *generalization error or test erro*r, that indicates how well the model performs on new, unseen data drawn from the same distribution as the training data (Goodfellow et al., 2016, p. 108). The training and test error are measured by the *cost or loss function* that compares the predicted bounding box outputs with the actual outputs. During training, the YOLO model optimizes *"for sum-squared error in the output of our model "(Redmon et al., 2016, p. 781),* which was adapted to address equal weighting of localization and classification errors and to account for empty grid cells in an image (Redmon et al., 2016, p. 781). The information from this cost function flows backward through the network using the backpropagation algorithm and enables the calculation of the gradient (Goodfellow et al., 2016, p. 200), which is then used to update the weights in to minimize the loss. The optimized weights are used for the validation of the model's performance on the validation set.

The performance, speed and accuracy of the model training process depend on the usage of various hyperparameters and configurations. Hyperparameters are not updated by the learning algorithm through the course of training (Goodfellow et al., 2016, p. 118) and therefore need careful experimentation. Important trainings settings are batch size, learning rate, momentum, and weight decay, as well as the choice of optimizer, loss function, and training dataset composition (Ultralytics, 2023). The explanation of the implemented basic settings can be taken from Table 28. These training settings are passed to the train function as argument.

Table 28 Training Configurations

Key	Arguments	dflt value	Explanation
`epoch`	Epochs	100	A training epoch refers to one iteration over the entire trainings set. (Hastie et al., 2009, p. 397)
`patience`	Patience	50	Epochs to bide if no progress is observed before discontinuing training (Ultralytics, 2023)
`batch`	Batch	16	Number of examples in each batch. Batch is a subset of the training data used in a single iteration of the training process. The use of batches allows the training process to make incremental updates to the model parameters and can help accelerate the training process.
`imgsz`	Image Size	640	*"Size of input images as integer or w,h" (Ultralytics, 2023)*
`lr0, lrf`	Learning rate	0.01, 0.01	Initial learning rate; final learning rate;
`optimizer`	Optimizer	'SGD'	Optimization algorithm: SGD (stochastic gradient descent) is set as default;
`momentum`	Momentum	0.937	The momentum algorithm uses a variable which represents the speed and direction at which the model parameters move during training (Goodfellow et al., 2016, p. 293).
`weight_decay`	Weight decay	0.0005	Weight decay is a regularization technique that helps to prevent overfitting during the training of a model. It involves adding a penalty term to the loss function that is proportional to the sum of the squares of the model's weights (Vasani, 2019). It is also known as L^2, ridge regression or Tikhonov regularization (Goodfellow et al., 2016).
`cos_ls`	Cosine Annealing learning rate scheduler	False	The cosine annealing technique is used to decay the learning rate during the training process. A cyclic pattern of learning rate adjustments is used, where the learning rate is periodically increased and then gradually decreased using the cosine function (Loshchilov and Hutter, 2016).

5.2.3. VALIDATION

The validation is the process in which the performance of a trained model is evaluated and the hyperparameters are adjusted (Goodfellow et al., 2016, p. 119). The performance of a ML algorithm depends on its capacity to

1) Minimize the training error,
2) Minimize the difference between training and test error.

These factors relate to the two central challenges in machine learning: underfitting and overfitting (Goodfellow et al., 2016, p. 109). Overfitting "*is given when the model lacks generalization of the data*" (Gonzalez Viejo et al., 2019, p. 9). DNNs such as YOLOv8 can recognize subtle patterns in the data, however, in the case where the training set is affected by noise, or it is undersized leading to sampling noise, the model tends to recognize patterns in the noise itself. These patterns are not useful for prediction in new examples (Géron, 2023; Gonzalez Viejo et al., 2019), resulting in a large gap between the training error and test error (Goodfellow et al., 2016, p. 110). *Underfitting*, on the other hand, "occurs when the model is not able to obtain a sufficiently low error value on the training set" (Goodfellow et al., 2016, pp. 109–110).

In this thesis the validation approach as proposed by Smith (2018) was adopted. In this approach, the arguments presented in Table 29, namely `learning rate, batch size, momentum`, and `weight decay` as well as `cyclical learning rates (cosine learning rate scheduler)` and `cyclical momentum`, are examined. This process involves analyzing the validation loss during training to detect indications of underfitting and overfitting to determine the optimal combination of hyperparameters. (Smith, 2018) Specifically, in the YOLOv8 training process the validation loss is computed at the end of each epoch. The training loss is calculated on the training set, while the validation loss is calculated on the validation set. Both the training loss ($train_{box\ loss}$, $train_{cls\ loss}$, $train_{dfl\ loss}$) and the validation ($val_{box\ loss}$, $val_{cls\ loss}$, $val_{dfl\ loss}$) are recorded in the results.csv file, which is the basis for the hyperparameter tuning. The generalization error is calculated as the difference between validation loss and the training loss (Smith, 2018, p. 3). The metrics and values related to the training process will be explained in the following section.

Metrics

The results.csv of each training run contains a table that lists the following values and metrics for each epoch (see Table 29).

Table 29 Metrics and values in results.csv related to the training process

Value/metric	Explanation
epoch	Index of the respective epoch
train/box_loss	Bounding box regression loss (sum of squared error loss) (Redmon and Farhadi, 2018) during training; difference between predicted box coordinates and ground truth annotations;
Train/cls_loss	classification loss (binary cross-entropy) (Redmon and Farhadi, 2018) during training
train/dfl_loss	the dual focal loss (DFL) addresses the class imbalance and class weakness problems (Hossain et al., 2021) during training
precision(B)	precision metric for bounding box predictions during training
recall(B)	recall metric for bounding box predictions during training
mAP50(B)	mean Average Precision (mAP) at IoU threshold of 50%. (Lihi Gur Arie, 2022) for bounding box predictions during training
mAP50-95(B)	mAP over different IoU thresholds, ranging from 50% to 95% (Lihi Gur Arie, 2022) during training
val/box_loss	Bounding box regression loss (Mean Squared Error) (Lihi Gur Arie, 2022) during validation; difference between predicted box coordinates and ground truth annotations
val/cls_loss	classification loss (binary cross-entropy) (Redmon and Farhadi, 2018) during validation
val/dfl_loss	the dual focal loss (DFL) addresses the class imbalance and class weakness problems (Hossain et al., 2021) during validation
lr/pg0	the learning rate for the first parameter group[10] during training
lr/pg1	the learning rate for the second parameter group during training
lr/pg2	the learning rate for the third parameter group during training

Furthermore, for each training run the precision against confidence graph (P-Curve), the precision against recall graph (PR-Curve), the F1 against confidence graph (F1-Curve) and the recall against confidence graph (R-Curve) are plotted. The F1-score is defined as:

$$F1 = \frac{2 \times Precision \times Recall}{(Precision + Recall)};$$ *Equation 5-1*

[10] The official documentation for YOLOv8 is not published yet, however based on the metrics it is inferred that it shares the same parameter groups as YOLOv5 - i.e. backbone, neck and head, each containing specific layers (Jocher (2023b).

With precision P and recall R defined as:

$$P = \frac{TP + TN}{(TP + FP + FN + TN)};$$ *Equation 5-2*

$$R = \frac{TP}{(TP + FN)}$$ *Equation 5-3*

Where TP denotes true positive values, TN denotes true negative values, FP denotes false positive values, and FN denotes false negative values. (Li et al., 2018) In object detection, recall is used to measure the ability of a model to identify all instances of a target class in an image or set of images. A high recall means that the model can identify most of the positive examples, indicating a low rate of false negatives, which are the positive examples that the model fails to detect (Hapke and Nelson, 2020). Precision indicates the proportion of predicted bounding boxes that are correctly assigned to the true positive class, i.e., the bounding boxes that accurately identify the object of interest (Hapke and Nelson, 2020). The F1 score is defined as the harmonic mean of precision and recall. Unlike the regular mean that assigns equal importance to all values, the harmonic mean assigns greater importance to lower values. Therefore, a high F1 score can only be achieved if the classifier has high precision and recall simultaneously. (Géron, 2023, p. 93)

Furthermore, the precision over recall curve can be summarized using the Mean Average Precision (mAP), an important metric in object detection (see Table 29). The mAP is obtained by calculating the maximum precision achievable at different recall levels. This allows for a fair evaluation of the model's performance. In multi-class scenarios, AP is computed for each class and then averaged to obtain the mAP. Additionally, in object detection, an IOU threshold is often used to determine if a prediction is correct. The mAP can be computed at a specific IOU threshold or across multiple IOU thresholds to account for different levels of accuracy. (Géron, 2023, p. 491) Intersection over Union or IoU, is a metric used to evaluate localization accuracy in object detection models and calculate localization errors. It measures the overlap between predicted and ground truth bounding boxes. The IOU is calculated by dividing the intersection area by the union area, providing an estimate of how well the predicted bounding box aligns with the original bounding box. (Kundu, 2023)

The corresponding plotted graphs and their interpretation are presented in Figure 67-Figure 71).

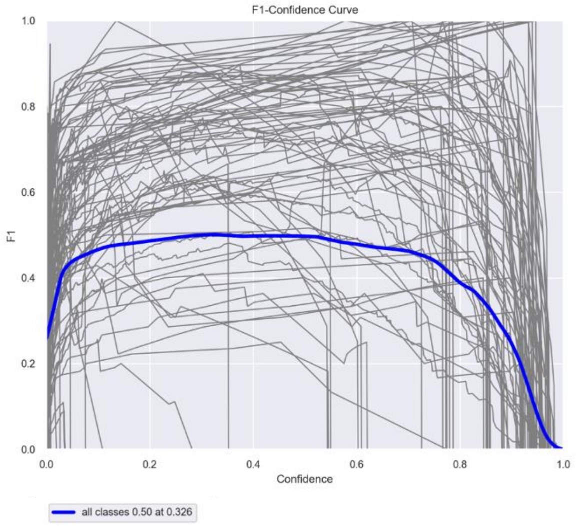

Figure 67 F1-Confidence Curve (Image by author).
The F1 against confidence plot shows how the F1 score varies depending on the confidence score. According to the equation, a high F1 score at a low confidence level indicates that the classifier makes both a lot correct as incorrect predictions, while a high F1 score at a higher level of confidence indicates that the classifier makes less predictions but with higher confidence in their correctness.

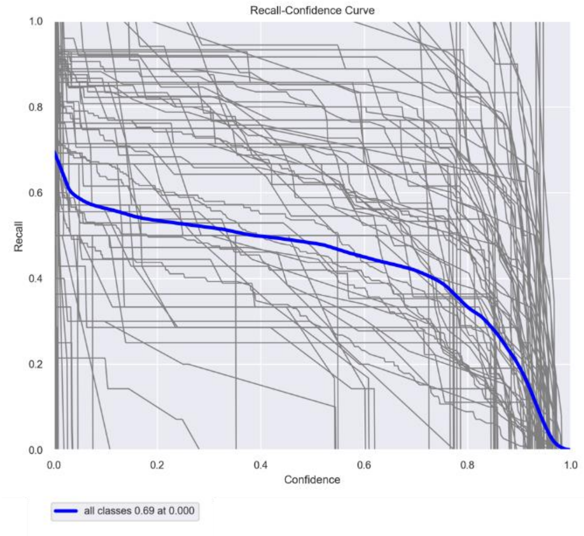

Figure 68 Recall-Confidence-Curve (Image by author).
Each point on the graph represents the trade-off between recall and confidence. A good model will have high recall values at high confidence levels, which will correspond to points on the upper left corner of the graphs. Accordingly, the model used in the figure is not well-performing.

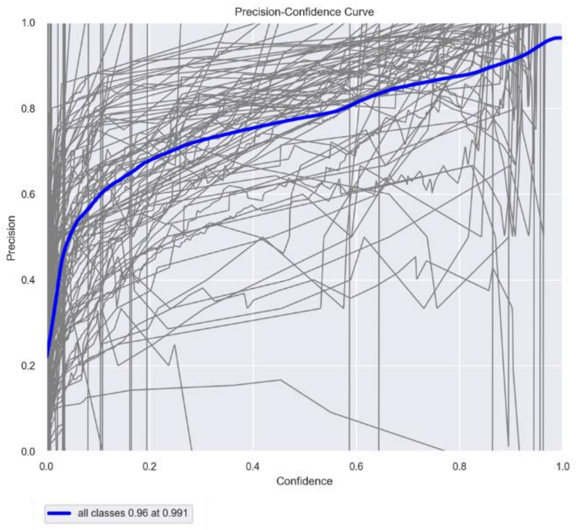

Figure 69 Precision-Confidence-Curve (Image by author).
Each point on the graph represents the trade-off between precision and confidence. A good model will have high precision values at high confidence levels, which will correspond to points on the upper left corner of the graphs.
The confidence threshold used by the model can be adjusted to change the trade-off between precision and recall. A higher confidence threshold will result in higher precision but lower recall, while a lower confidence threshold will result in higher recall but lower precision.

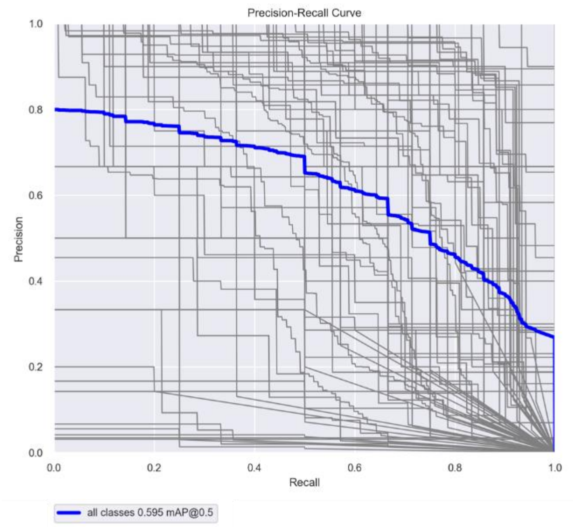

Figure 70 Precision-Recall-Curve (Image by author)
Each point on the PR curve corresponds to a different confidence threshold used by the model during object detection, which is a parameter controlling the trade-off between precision and recall. A well-performing model will have high precision and recall at a specific confidence threshold, corresponding to a point in the upper right corner of the PR curve. A model with low precision will produce many false positives, while a model with low recall will miss many true positives. As such, the PR curve can aid in identifying the optimal balance between precision and recall for a given confidence threshold.

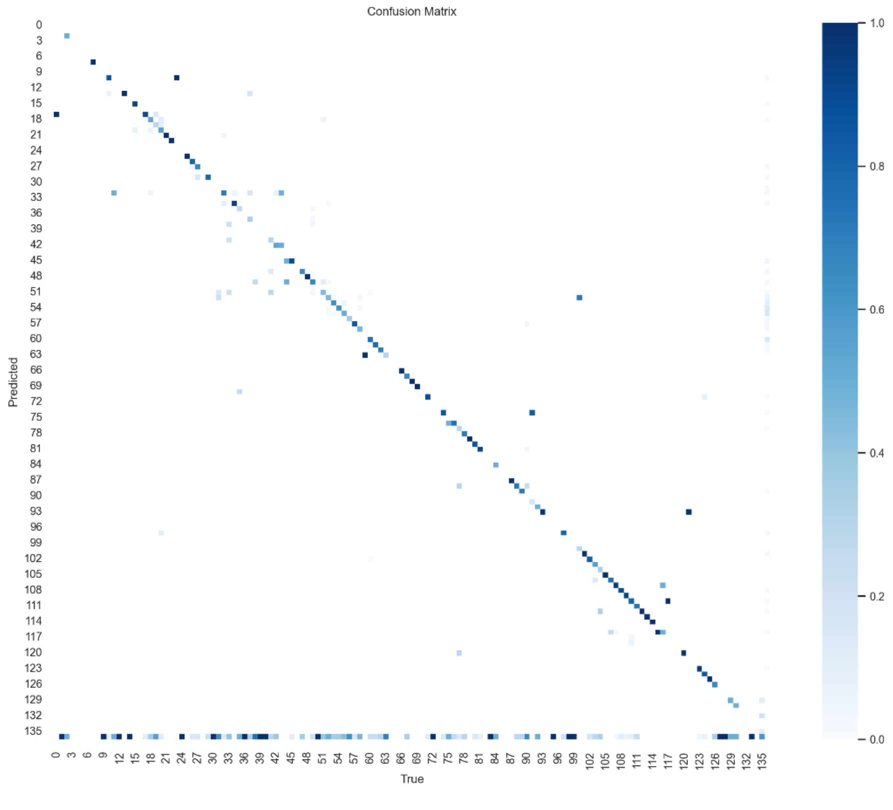

Figure 71 Confusion Matrix (image by author).
The confusion matrix is a tabular representation that compares the predicted classes of objects with their actual ground truth labels. Each row in a confusion matrix represents an actual class, while each column represents a predicted class (Géron, 2023, p. 91). To compare error rates rather than absolute numbers of error, that penalizes abundant classes, the normalized confusion matrix is regarded, which is obtained by dividing "each value in the confusion matrix by the number of images in the corresponding class" (Géron, 2023, p. 103). By normalizing the values, the confusion matrix accounts for differences in class sizes, making it possible to assess the error rates proportionally across classes. This is particularly important when dealing with imbalanced datasets, where some classes may have a significantly larger number of images compared to others.

5.2.4. TRAINING STRATEGY

In this thesis a total of eleven training runs were conducted. The nine training runs and their validation as well as the final testing were locally implemented in PyTorch using an NVIDIA RTX A4000 GPU. All training metrics, values and visualizations are attached to the digital annex.

Model 1

Training algorithms for deep learning models are usually iterative and thus require the user to specify some initial point from which to begin the iterations (Goodfellow et al., 2016, pp. 296–297). Currently there are no simple and easy ways to set hyperparameters – specifically, learning rate, batch size, momentum, and weight decay (Smith, 2018, p. 1). Therefore, in the first training run most of the default values were kept, only setting the input image size to 640 pixels and increasing the batch size to 32, while decreasing the workers from 8 workers per default to two.

```
#Model
model.train(data="data.yaml",
            task="detect",
            mode="train",
            epochs=100
            imgsz=640,
            workers=2,                  #                   reduced                   workers
            batch=32) # increased batch size
```

This is a common strategy to improve the training speed and efficiency of object detection models for a "fixed computational budget" (Smith, 2018, p. 7), because it can reduce the time spent on communication overhead between workers while keeping the GPU fully utilized. When the batch size is increased, more samples can be processed simultaneously, leading to better GPU utilization and faster training times. Generally speaking, larger total batch sizes result in higher test accuracy while smaller batch sizes yield lower test loss. (Smith, 2018, p. 7)

Table 30 Metrics and values of best performing epoch during training of model #1

	Train			Metrics				Validation		
#	**box_ loss**	**cls_ loss**	**dfl_ loss**	**Precision (B)**	**Recall (B)**	**mAP50 (B)**	**mAP50-95 (B)**	**box_ loss**	**cls_ loss**	**dfl_ loss**
79	0,9265	0,6166	0,99204	0,73058	0,51666	0,59517	0,35653	1,7444	1,3375	1,4421

Table 31 Metrics of best performing epoch in validation of model #1

Class	Images	Instances	Box (P	R	mAP50	mAP50-95)
all	226	2078	0.756	0.497	0.6	0.358

The first training run is used as benchmark to determine the consecutive configurations. From the metrics it can be observed that the model achieved relatively low losses in terms oof bounding box loss (box_loss), classification loss (cls_loss) and dual focal loss (dfl_loss), which indicates that the model is able to fit the training data well. Furthermore, in Table

30 the precision and recall values indicate only a moderate precision and recall during training. The precision and recall values on the unseen validation data in Table 31 suggest that the model can correctly identify a significant portion of positive instances. However, the mAP50 and mAP50-95 values show that the model's performance may vary across different detection thresholds. Furthermore, the mAP in training and validation do not significantly vary, suggesting that the model's performance in terms of object detection accuracy is consistent across both datasets. This may indicate that the model is not significantly overfitting or underfitting the data, as it is able to generalize well to unseen data. On the other hand, the training loss values are consistently lower than the validation losses, which is a sign that the model is overfitting the training data and does not generalize well to new data (Géron, 2023, pp. 133–134). This could be due to the model learning specific patterns or noise present in the training data that do not hold true in the validation data (Gonzalez Viejo et al., 2019, p. 9).

Model 2 and model 3

To adjust the overfitting, two general strategies are proposed by James et al. (2021): slow learning and regularization. Slow learning refers to a slow iterative learning process for example using gradient descent. (James et al., 2021, p. 434) However, in model 2 and 3 the second strategy, regularization, was adopted. *"Regularization is any modification we make to a learning algorithm that is intended to reduce its generalization error but not its training error"* (Goodfellow et al., 2016, p. 117). Therefore, the `learning rate` decreased from 0.01 by default to 0.001. Furthermore, the recommendation of Géron (2023) to use Adam (Kingma and Ba, 2014) for optimization, was considered. However, AdamW was eventually selected, which is a modification to the Adam optimization algorithm that aims to recover the original formulation of weight decay regularization (Loshchilov and Hutter, 2017, p. 1). It decouples the weight decay from the optimization steps taken with respect to the loss function. This modification allows for more flexibility in choosing the weight decay factor independently of the learning rate setting and *"substantially improves (Adam's) generalization performance*" (Loshchilov and Hutter, 2017, p. 1).

```
#model 2 ---> AdamW optimizer, learning
rate = 0,001, weight_decay = 0.01
model.train(data="data.yaml",
            task="detect",
            mode="train",
            epochs=100,
            imgsz=640,
            workers=2,
            batch=32,
            optimizer='AdamW',
            lr0=0.001,
            weight_decay=0.01)
```

```
# model 3: decrease learning rate,
workers --> default = 8
model.train(data="data.yaml",
            task="detect",
            mode="train",
            epochs=100,
            batch=32,
            imgsz=640,
            save=True,
            optimizer='AdamW',
            lr0=0.0007,  # decreased learning
rate by 30%
            weight_decay=0.001,#decreased
weight decay)
```

These adjustments led to a small improvement in the training losses, but to a decline of the validation losses (see Table 32). For further regularization, the `learning rate` was decreased by 30% in model 3, while the `workers` were set to the default value (workers = 8). The combination of increasing the number of workers and decreasing the learning rate can be effective in balancing computational efficiency and model performance. Furthermore, the `weight decay` was set to 10^{-3} as suggested by Smith (2018).

The configurations made in model 2 and 3 resulted in a small reduction in training and validation losses, but no significant improvements in the mAP50 or mAP50-95 were achieved (see Table 32-Table 35)

Table 32 Metrics and values of best performing epoch during training of model #2

	Train			Metrics						
#	**box_ loss**	**cls_ loss**	**dfl_ loss**	**Precision (B)**	**Recall (B)**	**mAP50 (B)**	**mAP50-95 (B)**	**box_ loss**	**cls_ loss**	**dfl_ loss**
86	0,8833	0,5271	0,98322	0,6111	0,5512	0,582	0,3574	1,7681	1,2854	1,5215

Table 33 Metrics of best performing epoch in validation of model #2

Class	**Images**	**Instances**	**Box (P**	**R**	**mAP50**	**mAP50-95)**
all	226	2078	0.611	0.551	0.583	0.359

Table 34 Metrics and values of best performing epoch during training of model #3

	Train			Metrics				Validation		
#	**box_ loss**	**cls_ loss**	**dfl_ loss**	**Precision (B)**	**Recall (B)**	**mAP50 (B)**	**mAP50-95 (B)**	**box_ loss**	**cls_ loss**	**dfl_ loss**
86	0,8711	0,5209	0,9785	0,7554	0,4967	0,5996	0,3579	1,7647	1,2613	1,4992

Table 35 Metrics of best performing epoch in validation of model #3

Class	**Images**	**Instances**	**Box (P**	**R**	**mAP50**	**mAP50-95)**
all	226	2078	0.756	0.497	0.6	0.358

Model 4

Reducing the learning rate resulted in an overall reduction in training and validation losses, so this approach was continued in Model 4. To decay the learning rate during the training the cosine annealing technique or `cosine learning rate scheduler` is used. The configurations of model 2 with an initial `learning rate` of 0.001 were used as base.

```
#model 4: introduce cosine learnrate scheduler
model.train(data="data.yaml",
            task="detect",
            mode="train",
            epochs=100,
            batch=32,
            imgsz=640,
            save=True,
            optimizer='AdamW', lr0=0.001, weight_decay=0.001,
            cos_lr=True) #introduced cos lr scheduler
```

This configuration resulted in an overall decline of the models performance, as seen in Table 36 and Table 37: the loss values have increased, while the precision, recall and mAP values in the validation set have deteriorated.

Table 36 Metrics and values of best performing epoch during training of model #4

	Train			Metrics				Validation		
#	box_ loss	cls_ loss	dfl_ loss	Precision (B)	Recall (B)	mAP50 (B)	mAP50-95 (B)	box_ loss	cls_ loss	dfl_ loss
56	1,0242	0,63336	1,0359	0,73212	0,49955	0,58145	0,34271	1,7835	1,2868	1,4758

Table 37 Metrics of best performing epoch in validation of model #4

Class	Images	Instances	Box (P	R	mAP50	mAP50-95)
all	226	2078	0.611	0.551	0.583	0.359

Model 5 and 6

In model 4, however, the gap between training and validation losses was reduced, indicating a good network convergence (Smith, 2018, p. 3) Therefore, the approach with the `cosine learning rate scheduler` is used as a starting point for further hyperparameter tuning. Specifically, the `epoch`, `batch`, `image size` and `learning rate` were tweaked, using the following approaches:

In model 5 the `workers` were set to 2 and the input `image size` was reduced to 512 pixels, while the number of `epochs` was increased to 150. Furthermore, since the training loss is higher than the validation loss, it must be assumed that some patterns are not generalized well to unseen data. Increasing the number of epochs to 150 allows the model to go through more training iterations, potentially allowing it to learn more complex patterns and improve its overall performance. Since there are limited computational resources available, increasing the number of epochs reduces the anaclity of the workers. By reducing the number of workers, the communication overhead between workers is minimized, resulting in faster training times. Additionally, reducing the size of the input image to 512 pixels can help reduce the model's memory requirements and computational complexity. The metrics and values of this configuration are found in Table 38 and Table 39.

Table 38 Metrics and values of best performing epoch during training of model #5

	Train			Metrics				Validation		
#	box_ loss	cls_ loss	dfl_ loss	Precision (B)	Recall (B)	mAP50 (B)	mAP50-95 (B)	box_ loss	cls_ loss	dfl_ loss
113	0,83595	0,48984	0,94943	0,65402	0,54315	0,57696	0,35531	1,7366	1,2284	1,5047

Table 39 Metrics of best performing epoch in validation of model #5

Class	Images	Instances	Box (P	R	mAP50	mAP50-95)
all	226	2078	0.654	0.543	0.578	0.356

The configurations in model 5 resulted in an improvement in loss values and validation metrics. Therefore, in model 6 only the `batch` size was reduced from 32 to 16. This change was adopted to allow for more frequent weight updates and potentially improving the model's generalization ability. It also helps mitigating memory limitations and reduce the computational burden, enabling smoother training on the limited hardware. The performance metrics and loss values are seen in Table 40 and Table 41

Table 40 Metrics and values of best performing epoch during training of model #6

	Train			**Metrics**				**Validation**		
#	**box_ loss**	**cls_ loss**	**dfl_ loss**	**Precision (B)**	**Recall (B)**	**mAP50 (B)**	**mAP50-95 (B)**	**box_ loss**	**cls_ loss**	**dfl_ loss**
113	0,8360	0,4898	0,9494	0,65402	0,54315	0,57696	0,35531	1,7366	1,2284	1,5047

Table 41 Metrics of best performing epoch in validation of model #6

Class	**Images**	**Instances**	**Box (P**	**R**	**mAP50**	**mAP50-95)**
all	226	2078	0.654	0.543	0.578	0.356

Model 7-9

Based on the performance of model 6 in model 7, 8 and 9 the parameters `epoch`, `learning rate` and `patience` were tweaked. Specifically in model 7 the `epochs` were increased to 500 and the `learning rate` was further reduced from 0.0007 to 0.0005. Based on the deterioration of the metrics in model 7, model 8 and model 9 used the configuration of model 6 and were used solely to test whether the performance of Model 6 could be further improved by increasing the epochs.

Table 42 Metrics and values of best performing epoch during training of model #7

	Train			**Metrics**				**Validation**		
#	**box_ loss**	**cls_ loss**	**dfl_ loss**	**Precision (B)**	**Recall (B)**	**mAP50 (B)**	**mAP50-95 (B)**	**box_ loss**	**cls_ loss**	**dfl_ loss**
84	1,0282	0,62262	1,022	0,65375	0,52818	0,58395	0,35345	1,6606	1,156	1,4252

Table 43 Metrics of best performing epoch in validation of model #7

Class	**Images**	**Instances**	**Box (P**	**R**	**mAP50**	**mAP50-95)**
all	226	2078	0.625	0.56	0.598	0.352

Table 44 Metrics and values of best performing epoch during training of model #8

	Train			**Metrics**				**Validation**		
#	**box_ loss**	**cls_ loss**	**dfl_ loss**	**Precision (B)**	**Recall (B)**	**mAP50 (B)**	**mAP50-95 (B)**	**box_ loss**	**cls_ loss**	**dfl_ loss**
137	0,93936	0,55566	0,	0,64231	0,55414	0,59669	0,35974	1,664	1,1216	1,4764

Table 45 Metrics of best performing epoch in validation of model #8

Class	**Images**	**Instances**	**Box (P**	**R**	**mAP50**	**mAP50-95)**
all	226	2078	0.735	0.509	0.596	0.359

Finally, in model 9 a patience of 250 epochs was implemented to avoid overfitting. Accordingly, the training was stopped early at 452 epochs and 7.147 hours of computing, as the model's performance on the validation set did not improve within a specified number of epochs. The training was stopped after 7,147 hours of computing.

Table 46 Metrics and values of best performing epoch during training of model #9

	Train			Metrics				Validation		
#	**box_ loss**	**cls_ loss**	**dfl_ loss**	**Precision (B)**	**Recall (B)**	**mAP50 (B)**	**mAP50-95 (B)**	**box_ loss**	**cls_ loss**	**dfl_ loss**
201	0,83303	0,48108	0,94848	0,6628	0,5652	0,59382	0,36145	1,6816	1,1053	1,4957

Table 47 Metrics of best performing epoch in validation of model #9

Class	Images	Instances	Box (P	R	mAP50	mAP50-95)
all	226	2078	0.664	0.565	0.594	0.36

Due to the limited time and resources of this work, the fine-tuning of the Yolov8s model was concluded after the ninth training run.

5.2.5. MODEL SELECTION

For the final model selection, the performance metrics of the different model configurations are compared as in the iterative training and validation process. Based on the metrics mAP, precision, recall and F1 score, model 6 and model 9 are shortlisted as they achieved the highest values in the metrics.

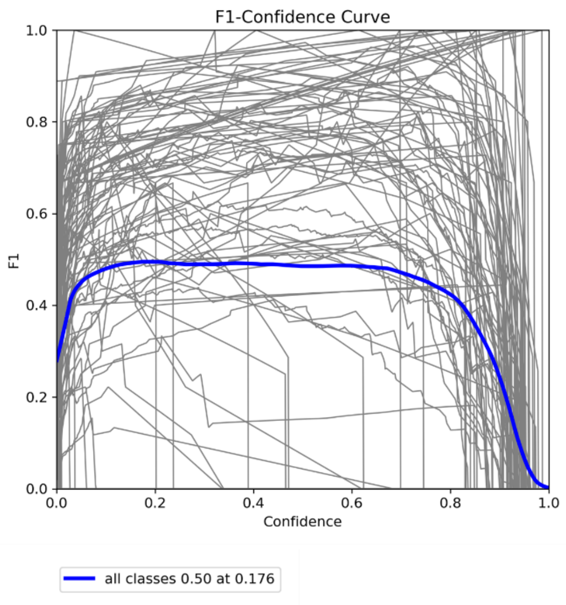

Figure 72 F1-Confidence-Curve of model #6 (image by author)

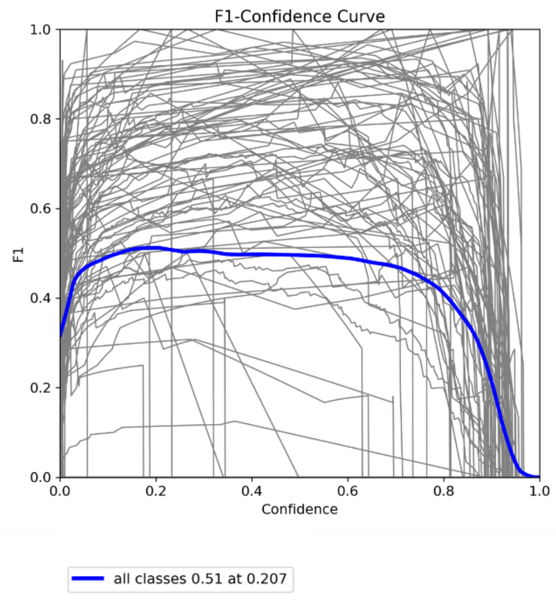

Figure 73 F1-Confidence-Curve of model #9 (image by author)

Regarding mAP50 (B), both models have the same value of 0.594, indicating similar performance in terms of average precision at 50% IoU. However, when considering mAP50-95 (B), model 6 has an insignificantly higher value of 0.361 compared to model 9's value of 0.36. According to these metrics, model 6 and model 9 have comparable performances, with some differences in precision, recall, and mAP50-95 (B). Furthermore, since the two models differ only in the number of epochs and patience, the computational requirements of each configuration, including inference speed and memory usage, is not considered as a determining criterion. Based on the F1-Confidence curves (Figure 72 and Figure 73), model 9 performed better, as it has a higher F1 score at a higher confidence than model 6. This implies that the model's predictions at higher confidence thresholds are more accurate in terms of both precision and recall and accordingly, model 9 is making fewer false positive and false negative errors when it is more confident about its predictions. Finally, the model 9 was selected for the test run.

5.3. TEST AND EVALUATION

In the final step of the machine learning pipeline, the performance of the selected model is evaluated against a retained test set. Subsequently, further approaches are assessed, and the limitations of the entire method are highlighted.

5.3.1. ASSESSMENT

The test run was performed with the test set consisting of 116 images with a total of 975 instances. The evaluation focuses on the detection performance and properties of the individual classes.

Detection performance: Precision P, recall R, F1 score and mAP

The model achieved a mean average precision (mAP) at 0.5 IoU threshold of 0.634, indicating a satisfactory overall performance in correctly detecting and localizing objects. Furthermore, both the precision and recall have higher values than in the validation.

Table 48 Test set performance metrics

Class	**Images**	**Instances**	**Box (P**	**R**	**mAP50**	**mAP50-95)**
all	116	975	0,721	0,596	0,634	0,371

The model achieved high precision (P and recall (R) values for several classes, indicating its ability to accurately detect those objects. For example, classes like „window-exterior-type22“ (P=0,953, R=1) ,“window-exterior-type55“ (P=0,809, R=1) and „window-exterior-type52“ (P=0,781, R=1) achieved perfect precision and recall.

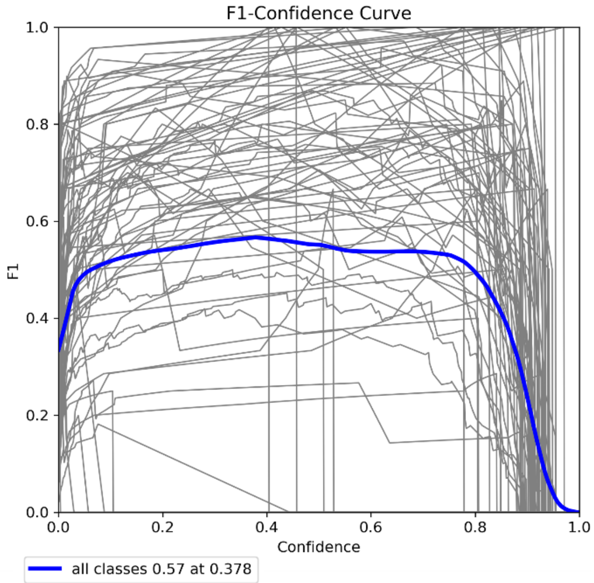

Figure 74 F1-Confidence Score in test-run (image by author)

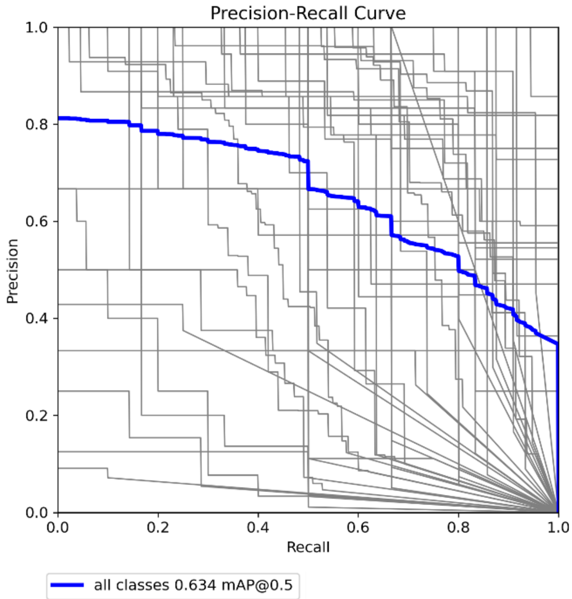

Figure 75 Precision-Recall-Curve in test-run (image by author)

The F1 curve for all classes starts at a relatively low point (0, 0.35) and reaches its maximum of 0.57 at a threshold of 0.378. Figure 74 reveals that the majority of class labels exhibit a comparatively high F1 score, indicated by the curves positioned above the blue average F1 score line. An F1 score close to 1.0 suggests that the model achieves a favorable trade-off between precision and recall, resulting in accurate predictions of positive instances for these classes. However, the overall F1 score of 0.57 for all classes is influenced by a few object classes that exhibit a notably low F1 score. In these classes, the model struggles to correctly detect positive instances, potentially due to an elevated presence of false positives or false negatives.

Likewise, the PR curve demonstrates a mixture of classes with favorable performance and a subset of classes with considerably inferior PR curves. This combination leads to an overall mAP@50 of 63.4% for all classes The PR-curve starts at with a precision of 81% at the lowest recall level (0% recall) but becomes less precise as it tries to capture more positive instances, meaning there is a trade-off between recall and precision. In summary, the PR-curve indicates a model that demonstrates relatively high precision at the beginning and overall good performance in terms of precision and recall trade-off.

Class-wise performanc

In the class-wise evaluation, it was found that the model's performance varies across different classes. The classes with the best performance can be found in Table 49.

Table 49 Metrics of best performing classes in test run

Class	Instances	Box (P	R	mAP50	mAP50-95):
window-exterior-type2	1	0,953	1	0,995	0,895
window-exterior-type55	2	0,809	1	0,995	0,824
window-exterior-type52	2	0,781	1	0,995	0,822
window-exterior-type3	3	0,491	1	0,995	0,796
door-interior-type11	1	0,711	1	0,995	0,796
window-exterior-type54	1	0,701	1	0,995	0,796
window-exterior-type1	2	0,734	1	0,995	0,748
window-exterior-type35	4	0,88	1	0,995	0,712
window-exterior-type53	1	1	1	0,995	0,697
window-exterior-type23	18	0,968	0,944	0,988	0,652

The classes with the best performance have high precision, recall, and mAP values due to several factors. These classes may have clear and distinctive visual features that facilitate discrimination from background and other objects. In addition, they may have sufficient training data for the model to learn robust features and object representations for accurate detection. In contrast, the worst performing classes are seen in Table 50:

Table 50 Worst performing object classes in test-run

Class	ID	Instances	Box(P	R	mAP50	mAP50-95):
window-exterior-type31	91	4	0	0	0	0
door-indoor-type4	31	3	1	0	0	0
door-interior-type8	51	2	1	0	0	0
window-exterior-type25	84	2	1	0	0	0
window-exterior-type44	104	2	1	0	0	0
door-indoor-glassdoor11	12	1	1	0	0	0
door-interior-type13	36	1	1	0	0	0
door-interior-type21	44	1	1	0	0	0
window-exterior-type16	74	1	1	0	0	0
window-exterior-type18	76	1	0	0	0	0
window-exterior-type29	88	1	1	0	0	0
window-interior-type8	135	1	1	0	0	0
window-interior-type9	136	1	1	0	0	0
door-interior-type12	35	2	1	0	0,0647	0,0194
window-exterior-type32	92	10	0	0	0,0411	0,0206
door-indoor-glassdoor3	19	7	0,0458	0,0262	0,0771	0,0377

In most of these classes, zero instances were detected, resulting in low precision, recall, and mAP scores, which indicates that the model does not effectively detect and localize instances of these classes. These classes may have visual attributes that are difficult for the model to distinguish, leading to recognition errors. Furthermore, insufficient training data for these classes could also contribute to poor performance, as the model is not sufficiently exposed to different examples for effective learning.

Similar conclusions are reached when the confusion matrix (see Figure 76) is used.

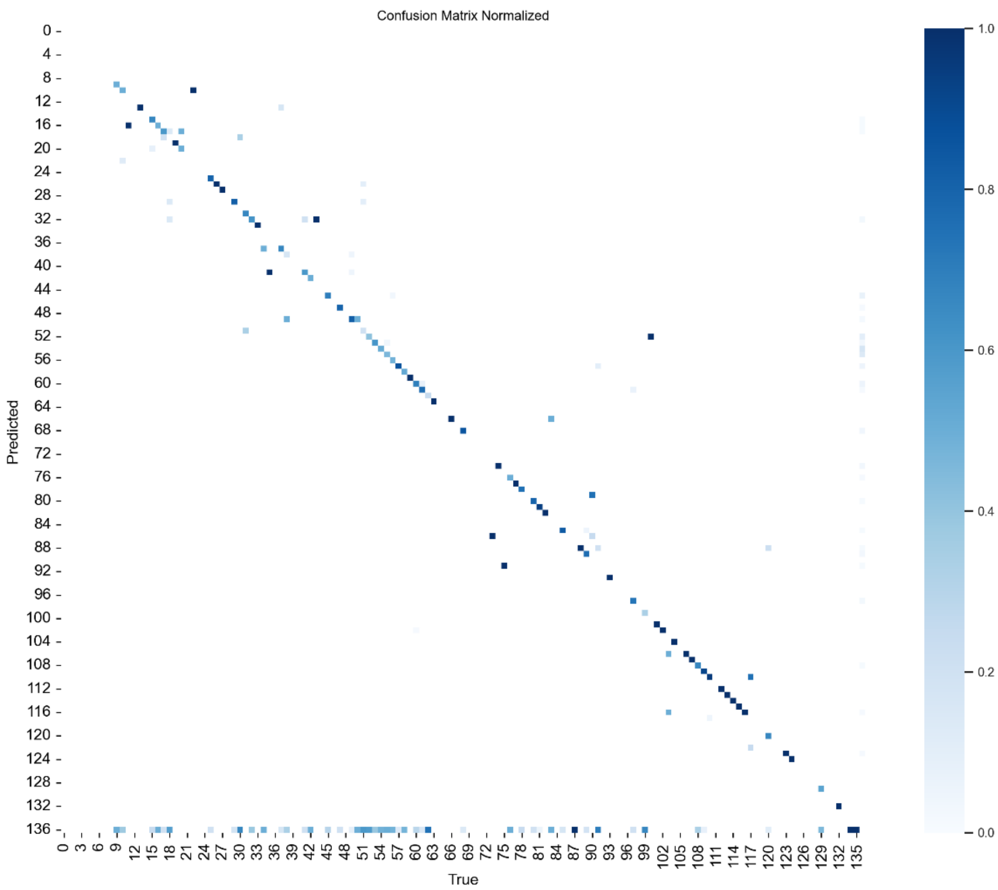

Figure 76 Normalized Confusion-Matrix of test-run (image by author).
Class IDs 1 to 52 describe door types, class IDs 53 to 59 describe lights, class ID 60-64 belong to sanitary, class IDs 65-136 describe window types.

From the diagonal in confusion matrix, it can be inferred that the majority of the classes are correctly predicted. However, the outliers allow the following conclusions to be drawn: Some classes are incorrectly assigned to another specific class with a high confidence. This can be recognized by a single point in a row and the coloring of the point in the graph. For these classes, more images or higher quality images are needed so that the features that lead to differentiation from the other component type can be better extracted by the model. Certain classes, such as class 135 (‚window-interior-type8') and class 136 (‚window-interior-type8') Class 136 and 135 lack fundamental distinguishing features, which is visible in the erroneous assignment to very different component types (doors, lights, windows).

Speed and efficiency

The model's speed was measured during different stages of the process. The preprocessing stage took an average of 1.8ms per image, the inference stage took 305.4ms per image, the loss calculation took 0.0ms, and the post-processing stage took 4.4ms per image. Overall, the model achieved a relatively fast speed during the inference stage, which is essential for real-time or time-sensitive applications.

Visual Assessment

Finally, the visual assessment of the test output is performed by analysing the images batch-wise. In particular, the following criteria are considered: Object localization, object classification, object recognition, accuracy and precision, generalization, and false positives and false negatives. When checking *object localization*, it is considered whether the model accurately locates the objects of interest in the image. This involves checking that the bounding boxes tightly enclose the objects and that there are no false positives or missed detections. Regarding the *object classification*, the assigned class labels were examined. Misclassifications or ambiguous designations are searched for. Furthermore, *object recognition* evaluates whether the model can recognize multiple objects in the same image. Overlapping or closely spaced objects must be recognized and distinguished as separate objects. Further, *accuracy and precision* refer to the predictions of the model. Attention is paid to discrepancies between ground truth annotations and objects recognized by the model. The *generalization* ability of the model can be determined by model performance on images with different backgrounds, lighting conditions, orientations, and scales. It is investigated whether the model can handle variations in real-world data that may be encountered during application for component recognition in different buildings. Last, the *false positive or false negative detections* that the model makes are identified. False-positive detections refer to objects that were incorrectly identified as being present, while false-negative detections refer to missing detections.
The batches and all predicted images are found in the digital annex.

Batch 0

In Batch 0, the overall performance can be assessed as very good. The model made errors in 3 out of 16 images. It is noticeable that in the first image, radiators were not localized despite having better image quality compared to others where heaters were distorted or poorly represented (see Figure 77). However, they have very low contrast with the wall. Additionally, there were instances of swapping similar window types, which can be attributed to the low resolution. Window types with the same basic shape (e.g., four- or five-sided) are usually differentiated based on the presence and number of mullions. If these mullions are not visible, incorrect assignment is likely.

Furthermore, a particular mismatch occurred where windows in the last few images were mistakenly identified as emergency lights (see Figure 78). This could be explained by one of the features of emergency lights being green. In this image, unlike other windows, trees are visible, creating a unique combination of white (light) and green (trees) as features for these windows, leading to a resemblance to emergency lights. Overall, good generalization is observed as objects are recognized in both heavily distorted (polar regions) and undistorted (central) areas, under various lighting conditions. The bounding boxes align with the ground truth annotations or even enclose the objects more tightly.

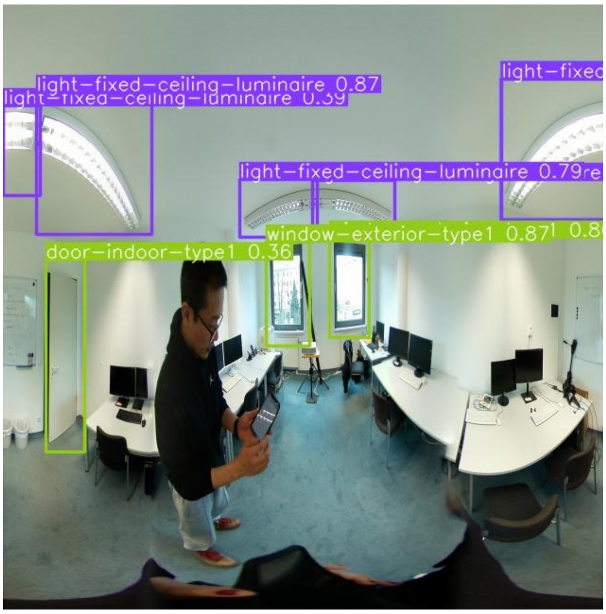

Figure 77 Sample image from batch 0 in the test run.
The radiators below the windows were not recognized. Image from (Bendiek Laranjo, 2023)

Figure 78 Sample image from batch 0 in the test run.
The windows are miscategorized as emergency lights.

Batch 1

Batch 1 performs similarly well as Batch 0, although more localization errors are found. First, ‘door-interior-type23’ was not localized, although other instances of the same class were present in the image (see Figure 79). This could be explained by the distortions of the door in the polar regions. Similarly, individual components in the edges of the image were not confidently recognized, e.g., in Figure 80 the cut-off door was not recognized, and in the same image a window was not correctly localized despite being displayed undistorted. However, generally a good object recognition is noticed, as several object categories are correctly detected on the images and tightly captured in bounding boxes. When examining Batch1, individual errors in the original dataset were noticed: The windows in Figure 82 are labeled as 'window-exterior-type59' in the TUDataset but were correctly detected by the model as 'window-exterior-type61', suggesting high precision in this object class. Similarly, the right orange door in Figure 81 was incorrectly labeled in the annotation process, but correctly identified as ‘door-interior-type23’ in the model. In the same picture another error is found, as the ceiling light is localized twice. The dataset will be corrected accordingly.

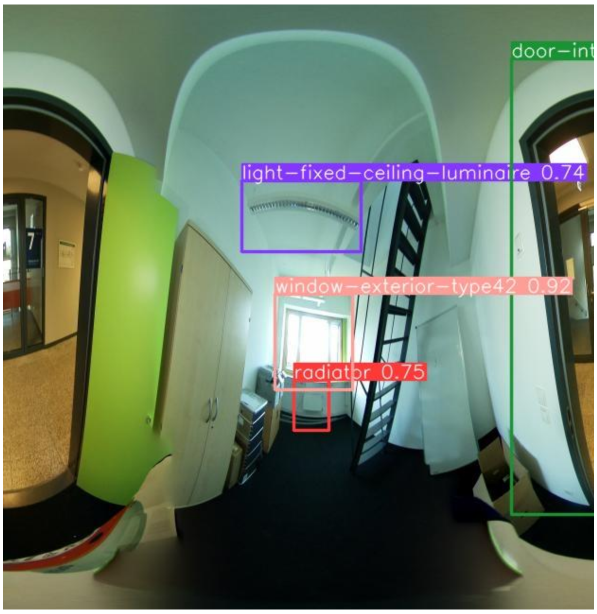

Figure 79 Sample image from batch 1. The door in the left edge is not recognized.

Figure 80 Sample image from batch 1 in the test set.
The cut off part of 'door-indoor-glassdoor15' was not recognized in the right edge of the image. Furthermore, the smaller window above the 'window-exterior-type39' was not localized

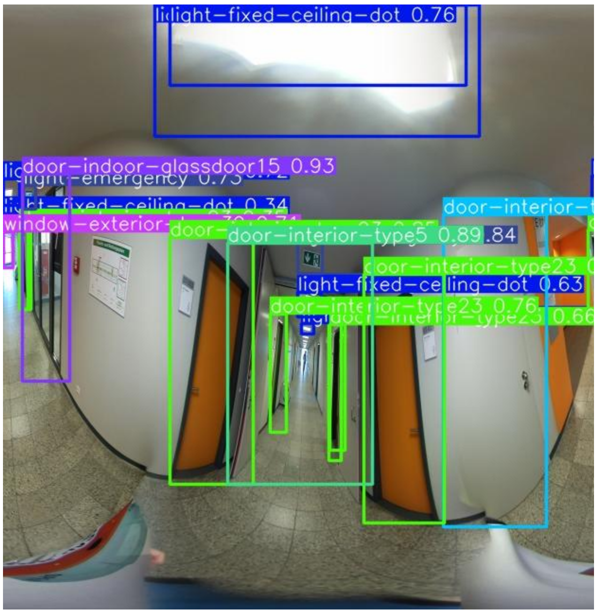

Figure 81 Sample image from batch 1 in the test set.
The model correctly predicted the label 'door-interior-type23' for the right orange door. However, the ceiling-light was localized twice.

Figure 82 Sample image from batch 1 in the test set.
The windows were correctly labeled as Type 61.83

Batch 2

Among the considered batches, Batch 2 demonstrates the fewest errors. All relevant objects are accurately localized and tightly enclosed by bounding boxes, with no false detections observed. The model displays strong object recognition capabilities, successfully identifying and distinguishing multiple objects in an image, even when they are closely spaced or at varying distances from the viewpoint. The evaluation of this batch indicates that the model generalizes well, effectively recognizing the same type of window in different lighting conditions, orientations, and scales. However, errors are observed in the classification of objects. Specifically, there appears to be a difficulty in distinguishing between 'Window-Exterior-Type50' and 'Window-Exterior-Type57'. The former has eight cutouts per sash in the center field, while the latter has six window cutouts per sash in the same area. Inconsistencies in the dataset annotations contribute to the model's challenge in accurately distinguishing between these two object classes.

Figure 84 A representative image from the TUDataset, which is not included in the test set. Depicting windows belonging to the 'window-exterior-type50' class with eight cutouts per sash in the center field. Image from (Bendiek Laranjo, 2023)

Figure 85 Image from batch 2 in test set. The labels of these windows are wrongly predicted as 'window-exterior-type50'.Since these windows have six cut-outs per sash in the central part, they correctly belong to the class 'window-exterior-type57'.

5.3.2. EVALUATION

Overall, the scope of this thesis was achieved by the model. The YOLOv8s model trained here demonstrated promising performance in facilitating the reuse process by accelerating the recognition of components. The approach assumes that 360° images are increasingly used for documenting the as-built condition of structures. The time for image generation is not considered in the component recognition process as the images serve other purposes besides the reuse assessment. The model's current state allows for accurate determination of reusable components, enabling an initial cost estimate for deconstruction. Additionally, the model significantly reduces the time required for component inventory compared to analog methods, potentially resulting in savings in labor costs and time. Further research could potentially be conducted to explore these saved costs and time. The model in this study deals effectively with distortions, by successfully recognizing component types, even when presented in different conditions and deformations, and accurately assigning them to the correct class. It achieved satisfactory detection and localization results, with high precision and recall for several classes. However, there is room for improvement, especially in classes with low F1 scores and poor performance. Addressing the misclassifications, reducing false positives and false negatives, and increasing the training data for challenging classes would enhance the model's ability to accurately recognize components and further accelerate the reuse process.

Strategies to address these issues could include the application of dropout regularization to prevent overfitting, dataset augmentation to increase the sample size, and fine-tuning the model on a larger and more diverse dataset. Dropout is a regularization technique that involves randomly dropping out (removing) hidden and visible units from the network, along with all their connections (Nitish Srivastava et al., 2014, p. 1930). Data augmentation is a good solution to address the large number of object categories and intra-class variations in the TUDataset that arise from different representations of the components in the ERP. A large discriminative power is required from the detector to distinguish between subtly different interclass variations (Liu et al., 2018a, p. 5) that can be achieved by feeding a diverse set of examples of each class to the model (Rakhshan et al., 2021a, p. 7). Additionally, improvements in camera quality or image enhancement techniques, such as denoising, deblurring, or contrast adjustment, can contribute to better representations of the components, leading to better feature extraction and enhanced intra-class distinction. Finally, normalizing the dataset and exploring alternative validation strategies are also important factors to enhance the model's performance. Normalization and data cleaning are necessary because errors in the annotation and inconsistencies in the label designation were noticed during the assessment of the model. Lastly, in this thesis holdout validation is used, where a "holdout" subset of the training data is used to evaluate multiple candidate models (Géron, 2023, p. 31).

However, a small validation set may lead to imprecise model evaluations, while a large validation set reduces the size of the remaining training set. Repeated cross-validation with multiple small validation sets solves this, but increases training time, as each model is evaluated on each validation set, and their evaluations are averaged for more accurate performance measurement. (Géron, 2023, p. 31)

For smaller data sets, unsupervised pre-training helps to prevent overfitting40 , leading to significantly better generalization when the number of labelled examples is small, or in a transfer setting where we have lots of examples for some 'source' tasks but very few for some 'target' tasks. Once deep learning had been rehabilitated, it turned out that the pre-training stage was only needed for small data sets. (LeCun et al., 2015, p. 439)

6 CONCLUSION

6.1. SUMMARY AND CONTRIBUTIONS

The thesis "Implementing the principles of Circular Economy in the Architecture, Engineering and Construction (AEC) sector: About the identification of reusable components using 360° Scans and Machine Learning" aims at advancing circular economy (CE) practices in the built environment using machine learning in combination with 360° images. The thesis is motivated by the need to promote adopting a circular economy in the construction industry, considering its resource-intensive nature and environmental impact.

The thesis defines Circular Economy in the Built Environment as adopting strategies at every stage of a building's life cycle to maximize the retention of materials within a closed loop. This thesis focuses on the Reuse strategy. In addition, the underlying key concepts of artificial intelligence, machine learning, neural networks, computer vision, and 360° images are defined to provide the necessary theoretical foundations for object detection using a convolutional neural network in the practical implementation of the thesis.

A systematic literature review explores the state of the art in circular economy implementation in the built environment. Research trends are identified using the scientometric software VOSViewer, and implementation barriers are discussed. The analysis revealed seven trends in the research field of CE in the AEC sector. Furthermore, the implementation of circular economy in the construction practice was examined on the micro, meso, and macro levels. The role of machine learning in enabling a circular built environment is also analyzed, including its applications and potential for component reuse.

For the methodology of this thesis the process of reuse is formalized by creating a process framework. Due to the lack of a standard, reusable components are identified based on a field study of component exchanges, and it is determined which components should be recognized by the machine learning algorithm and what their distinguishing characteristics are. Windows, doors, lights, heaters, and sanitary objects (toilet, sink, pissoirs) were specified as selection. Machine learning techniques for component identification were then analyzed, and the specifics of using 360° imagery were addressed. Based on the presented reuse process, the need for cost- and time-efficient solutions for inventory is determined, and the scope for machine learning applications is defined.

The one-stage object detection model Yolov8 was chosen for this thesis task. The practical implementation of the machine learning pipeline is presented in detail, covering data generation, annotation, training, validation, and testing. The practical part of the work encompasses all steps from data collection to creating a custom dataset, training and validation of different YOLOv8 model configurations, and testing. The resulting TUDataset consists of approximately 2,400 360° images in Equirectangular projection and 136 object classes. The selected model configuration achieves a mean Average Precision at IoU 0.5 of 63% and a mean Average Precision at IoU 0.5 to 0.95 of 37%. Finally, the model is evaluated, and various configurations are proposed. Overall, this thesis contributes to the transition towards a circular economy in the construction industry by proposing a practical solution for identifying reusable building components. It combines interdisciplinary approaches, incorporating machine learning and 360° imaging, to address the challenges of resource utilization and waste reduction.

6.2. CONTRIBUTIONS

The effectiveness of CNNs in AEC applications is heavily reliant on the quantity of data used during training. To prevent the problem of overfitting, a substantial amount of data is typically needed for training. Unfortunately, many CNN-based approaches designed for the AEC sector encounter this problem because they rely on a relatively small amount of training data, often gathered through conventional cameras. (Darko et al., 2020, p. 14) The thesis provides a fully labeled dataset of 360° images, facilitating research and practical applications in object detection. To the authors best knowing it is the first Object Detection dataset generated in the Technical University of Dresden.

Furthermore, this work demonstrates the effectiveness of using 360° images for object detection tasks, showcasing their potential in accurately identifying objects. Additionally, the thesis demonstrates the benefits of incorporating machine learning techniques into the inventory process, highlighting how it accelerates and improves the efficiency of inventory management.

Furthermore, to the author's best knowledge it is the first attempt to use object detection in 360° images with the purpose of enabling component reuse.

6.3. DISCUSSION OF RESULTS

The results of this work will be summarized and critically reviewed below.

First, the literature review has shown that the field of CE in BE is developing very rapidly. The research focuses on analyzing barriers to CE, the different strategies, and the increasing connection of CE with digital technologies like BIM or GIS. There is a significant misalignment between research and practice: while in research, very tangible strategies and frameworks are proposed and evaluated, in practice, these take place only in individual projects. Despite the urgency and already existing guidelines (e.g., on the EU level), a comprehensive strategy is not available and requires a turnaround of politics and the economy. A similar conclusion is drawn from the analysis of CE practice projects implemented mainly on the micro (component or material level) and meso level (construction project level). The least project approaches can be found at the regional or macro level. Nevertheless, it was found that digital approaches for implementing CE strategies are increasingly being proposed in research. According to the "two birds with one stone" principle, the low level of digitization and the slow CE implementation could thus be advanced.

The author of this thesis agrees with (Pomponi and Moncaster, 2017), that implementing CE in the construction industry should focus on assessing and mining existing buildings rather than new construction. In terms of planning for circularity, from the considerations in this thesis, several obstacles arise concerning reuse, including:

The lack of accurate data on the current state. Often, reliable information about the materials used or product manufacturers is unavailable. This is partly due to inadequate documentation of subsequent modifications to the building or a lack of centralized management and accessibility of such documentation. Detailed measurements and condition descriptions need to be included.

The limited awareness among industry practitioners regarding the potential for reusing building components. This results in the potential of components being recognized only when they become "waste" and a cost burden. Late identification of potential components poses significant logistical challenges. Planning construction projects requires considerable time and lead time for implementation. To incorporate a reusable component into the planning, it must already be cataloged, and its availability date must be determined. Suppose a component is identified for reuse shortly before or even after its installation. In that case, it can only be included in the planning and re-enter the circular process after the completion of the project. This leads to storage times that have a negative impact on costs and space requirements. Early identification of reuse potential is, therefore, necessary to save costs.

The reliance of component documentation on analog and fragmented solutions. Although individual tools like Concular or Madaster are available, the author considers them inefficient for rapid component capture. The "Material Passport" approach by Concular requires each component to be photographed and its attribute template to be filled out manually. Madaster, on the other hand, assumes the existence of an as-built BIM model or Excel cadaster and is, therefore, rarely applicable to Urban Mining projects.

The need for easily accessible information for planning with reusable components. Although component exchanges exist as described in Chapter 4, they do not meet the quality standards required for planning purposes. Currently, there is a lack of standardized formats for cataloging components andcadasters that capture the building stock. It would also be highly advantageous to provide digital drawings or models in addition to images for each component.

The approach presented in this thesis serves as a proof-of-concept, showcasing the potential use of 360° images and artificial intelligence for Urban Mining. It demonstrates the suitability of 360° cameras for inventory management with the purpose of component detection. Furthermore, it shows that sufficient accuracy can be achieved using conventional object detection models on equirectangular projections. Machine learning enables significant time savings and sufficient precision in identifying component classes and, to a lesser extent, component types within a class. However, further fine-tuning and revision of the TUDataset are necessary. The approach presented in this thesis serves primarily as a solution to overcome the analog and time-consuming work methods and is not a final concept but should be integrated into a comprehensive proposed framework, to be outlined in the 6.5 Future Research section.

6.4. LIMITATIONS

Firstly, it is important to note that the study focuses solely on reuse, representing a highly specific and limited case within the broader context of the circular economy strategies employed throughout the entire building lifecycle.

Regarding the data, it should be noted that the selection of components examined in this research represents only a small subset, and a broader range of non-destructive, non-toxic components can potentially be reintegrated into a circular economy. This limitation stems from the assumption that all areas and spaces within a building are accessible. Consequently, only the components captured by the camera can be identified. Therefore, introducing similar uncertainties in the number of components as in traditional on-site inspections and component identification processes.

Regarding the model used in this study, it is crucial to highlight that, thus far, the model has only detected the component type. Further research and analysis should be conducted to extract additional crucial information, such as the condition and, most importantly, the dimensions of the components. Additionally, the current data analysis did not consider the location of the components within the building. However, it is recommended that future research considers this aspect. For instance, leveraging the capabilities offered by Open Experience, integrating floor plans, and linking them with the captured images while specifying the field of view would enable more precise and efficient localization of the building components within the structure.

In terms of the model employed in this thesis, the objective was to demonstrate the suitability of 360-degree images as a foundation for object detection. The training of the model aimed to achieve a high level of precision and performance. However, it is important to acknowledge that further training is necessary to develop a model that can compete with existing state-of-the-art models in terms of performance and accuracy.

Furthermore, it should be noted that various approaches integrating spherical layers into convolutional neural networks have been proposed in related literature. These approaches were not explored in this research due to resource limitations. Nonetheless, they should be regarded as important references and potential alternatives for future investigations. Lastly, it is worth mentioning that no comparative model was implemented in this thesis. As a result, the performance values of the chosen model can only be evaluated compared to similar publications. The lack of further performance metrics on the TUDataset represents a significant limitation, as it hinders the ability to numerically compare the results. Therefore, it is evident that further research is needed to incorporate and evaluate additional models, providing a more comprehensive analysis and understanding of the topic.

In conclusion, while this thesis has contributed valuable insights into extracting information from images within the context of reuse in the building construction sector, it is essential to acknowledge and address the limitations discussed. A more comprehensive and robust understanding of the subject matter can be achieved by recognizing these limitations and incorporating them into future research endeavors. Due to the lack of previous research in this field, this thesis provides a groundwork to be built on.

6.5. FUTURE RESEARCH

The identified problems of unreliable information, lack of tools and standards for rapid data acquisition, and the provision and storage of component information should be considered interdependent and require a holistic solution. The author views Building Information Modeling (BIM) as a suitable technology that should be at the center of the solution, encompassing all relevant information. Therefore, technical solutions for implementing Circular Economy (CE) strategies should consider the interfaces with the BIM model from the outset. The ultimate goal is to create an as-built model of existing buildings, serving as a central database that incorporates all information and generates further insights. The following research approaches are considered:

Geometric modeling through 3D reconstruction

Further efforts to automate inventory processes using machine learning should be pursued. Existing research in 3D reconstruction aims to reconstruct components and their connections as-built using photogrammetry, machine learning, and data from LIDAR point clouds and 360° images (Fujita and Kuki, 2016; Gordon et al., 2023; Wang and Cho, 2015). If these components are not only created as 3D representations but also as BIM objects, the advantages of BIM can be utilized, with components serving as building passes or material passes.

Information enrichment through BDA (Big Data Analytics) and ML (Machine Learning)
Efforts should be made to refine object detection models to extract geometric, material, and static information from images. Additionally, this work exclusively employed object class detection, but future possibilities include object instance detection, which can identify specific component models based on manufacturer specifications. Manufacturer specifications serve as sufficient planning references for component reuse. Specific instance identification could also drive recycling programs. For example, based on a manufacturer's product catalog, it is conceivable to identify the specific component types used in a deconstruction project and have the manufacturer remove and refurbish them. This scenario could become relevant due to the increasing costs of primary resources for manufacturers. However, data and object detection datasets are required for this research endeavor, and its procurement should also be a focus of future work.

BDA tools have already been used in research to manage information from various digital and analog (historical) sources and building data has to be combined with urban data and component data. Therefore, research is needed to implement these technologies to make building information, such as data from building authorities, available. In addition to information acquisition, storing information in the model is important. Significant research is needed to standardize component descriptions for reuse and generating material passes. Currently, DIN SPEC 91484 is being developed to "a procedure for capturing construction products as a basis for assessing their reuse potential before demolition and renovation works, ensuring that all market participants have sufficient and consistent data depth at all stages of the value chain" (Deutsches Institut für Normung e.V., 2022 translated by author). Nevertheless, future research could focus on implementing these standards in BIM ontologies.

Deriving information from the BIM model
Material passes and material registers, integration with LCA (Life Cycle Assessment) tools and RMMs (Resource Management Models): Research is needed to determine the output format, scope, and legal binding of material passes. Additionally, a comprehensive concept for macro-level inventory is necessary, and further research is needed to promote the integration of BIM and GIS (Geographic Information System).

The BIM model is a database from which components can be available on component exchanges. While BIM online catalogs exist, they have yet to be utilized for the commercial distribution of used components or as a planning foundation. For example, BIMObject [11] provides CAD and DWG files for various component products. However, these platforms have the disadvantage of lacking standardized information content for components.

[11] https://www.bimobject.com/de

In conclusion, the author recognizes the need for research on the tracking of components. Due to the limited establishment of Circular Economy (CE) in the built environment, there are few or no long-term studies on the behavior of reused components. The existing approaches to track components using Blockchain technology (BCT) and monitor component behavior with sensors should be further explored in future studies.

7 References

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I SOURCECODE DOCUMENTATION

MAIN PROGRAM FOR MODEL TRAINING (MAIN.PY)

```
from ultralytics import YOLO
from ultralytics import YOLO
from fpdf import FPDF

def save_table_to_pdf(data, filename):
    pdf = FPDF()
    pdf.add_page()
    pdf.set_font("Arial", size=12)

    # Set table cell width and height
    cell_width = pdf.w / len(data[0])
    cell_height = pdf.font_size + 2

    # Add rows to PDF
    for row in data:
        for item in row:
            pdf.cell(cell_width, cell_height, txt=str(item), border=1)
        pdf.ln()

    # Save PDF
    pdf.output(filename)

if __name__ == '__main__':
    import multiprocessing as mp

    mp.freeze_support()

    # Load a model
    model = YOLO("C:/Users/anaom/OneDrive/Dokumente/01 TUD/Diplom/Experiments/Ana/runs/de-
tect/train9/weights/best.pt")

    model.train(data="data.yaml",
                task="detect",
                mode="train",
                epochs=100,
                imgsz=640,
                workers=2,
                batch=32)  # train the model

    #model 2 ---> AdamW optimizer, learning rate = 0,001, weight_decay = 0.01
    #model.train(data="data.yaml",
                #task="detect",
                #mode="train",
                #epochs=100,
                #imgsz=640,
                #workers=2,
                #batch=32,
                #optimizer='AdamW',
```

```
            #lr0=0.001,
            #weight_decay=0.01
            #scheduler=StepLR(optimizer, step_size=50, gamma=0.1))

# model 3: decrease learning rate, workers --> default = 8
#model.train(data="data.yaml",
            #task="detect",
            #mode="train",
            #epochs=100,
            #batch=32,
            #imgsz=640,
            #save=True,
            #optimizer='AdamW',
            #lr0=0.0007,  # decreased learning rate by 30%
            #weight_decay=0.001,#decreased weight decay)

#model 4: introduce cosine learnrate scheduler
#model.train(data="data.yaml",
            #task="detect",
            #mode="train",
            #epochs=100,
            #batch=32,
            #imgsz=640,
            #save=True,
            #optimizer='AdamW',
            #lr0=0.001,
            #weight_decay=0.001,
            #cos_lr=True) #introduced cos lr scheduler

# model 5: increase epochs to 150, decrease image size, decrease learning rate
#model.train(data="data.yaml",
        #task="detect",
        #mode="train",
        #epochs=150, #increase epochs
        #imgsz=512, #decrease image size
        #workers=2,
        #batch=32,
        #optimizer='AdamW',
        #lr0=0.0007,
        #weight_decay=0.001,
        #cos_lr=True)


#model 6: decrease batch size
#model.train(data="data.yaml",
            #task="detect",
            #mode="train",
            #epochs=150,  # increase epochs
            #imgsz=512,  # decrease image size
            #workers=2,
            #batch=16, #decrease batch size for generalization
            #optimizer='AdamW',
            #lr0=0.0007,
            #weight_decay=0.001,
            #cos_lr=True)
```

```
# model 7: increase epochs, decrease learning rate
#model.train(data="data.yaml",
        #task = "detect",
        #mode = "train",
        #epochs = 500,  # increase epochs
        #imgsz = 512,
        #workers = 2,
        #batch = 16,
        #optimizer = 'AdamW',
        #lr0 = 0.0005, #learning rate -30%
        #weight_decay = 0.001,
        #cos_lr = True)

# model 8: same config as model 6, but increase epochs
#model.train(data="data.yaml",
            #task="detect",
            #mode="train",
            #epochs=500,  # increase epochs
            #imgsz=512,
            #workers=2,
            #batch=16,
            #optimizer='AdamW',
            #lr0=0.0007,
            #weight_decay=0.001,
            #cos_lr=True)

# model 9: same config as model 6, more epochs
#model.train(data="data.yaml",
            #task="detect",
            #mode="train",
            #epochs=500,# increase epochs
            #patience=250,#set patience
            #imgsz=512,
            #workers=2,
            #batch=16,
            #optimizer='AdamW',
            #lr0=0.0007,
            #weight_decay=0.001,
            #cos_lr=True)


#config 10: final config
#model.train(data="data.yaml",
            #task="detect",
            #mode="train",
            #epochs=500,  # increase epochs
            #patience=250,  # set patience
            #imgsz=512,
            #workers=2,
            #batch=16,
            #optimizer='AdamW',
            #lr0=0.0007,
            #weight_decay=0.001,
            #cos_lr=True
```

```
                #amp = True,
                #droput = True)


    #Validate the model --> set test set to val set
    #model = YOLO("C:/Users/anaom/OneDrive/Dokumente/01 TUD/Diplom/Experiments/Ana/runs/de-
tect/train9/weights/best.pt")
    #metrics = model.val( save=True) #batch=16,
                        #iou=0.5,
                        #conf=0.005)
    #metrics.box.map    # map50-95
    #metrics.box.map50  # map50
    #metrics.box.map75  # map75
    #metrics.box.maps   # a list contains map50-95 of each category
```

DATA YAML


```yaml
train: C:\Users\anaom\OneDrive\Dokumente\01 TUD\Diplom\Experiments\Ana\TUDataset\train
val: C:\Users\anaom\OneDrive\Dokumente\01 TUD\Diplom\Experiments\Ana\TUDataset\valid
test: C:\Users\anaom\OneDrive\Dokumente\01 TUD\Diplom\Experiments\Ana\TUDataset\test

nc: 136
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II OVERVIEW

Keywords *Circular Economy, component reuse,*
AEC, built environment,
artificial intelligence, machine learning, object detection,
360° images, panorama images

Author Ana Bendiek Laranjo

Title Implementing the principles of Circular Economy in the AEC sector: About the identification of reusable components using 360° Scans and Machine Learning

Location Technical University Dresden

Faculty of Civil Engineering

Institute for Construction Informatics

Bibliographic Information: 2023, 141 (211) Pages, 76 Figures, 59 Tables

The thesis aims to advance circular economy practices in the construction industry using machine learning and 360° images. It addresses the research gap at the intersection of machine learning, circular economy, and 360° images for identifying reusable components in the built environment. The thesis defines Circular Economy in the Built Environment and explores its implementation in the construction practice at various levels. It analyzes the role of machine learning in enabling a circular built environment, including its applications and potential for component reuse. The methodology formalizes the process of reuse, identifies reusable components based on a field study, and analyzes machine learning techniques for component identification using 360° imagery. The practical implementation covers data generation, annotation, training, validation, and testing, resulting in a dataset with high precision. Overall, the thesis contributes to transitioning towards a circular economy in construction by proposing a practical solution for identifying reusable building components, combining interdisciplinary approaches of machine learning and 360° imaging to address resource utilization and waste reduction challenges.

III ANNEX DIRECTORY

IV DIGITAL ANNEX DIRECTORY

Annex	Subfolder	Definition
TUDataset	test	Test set including images and labels
	train	Trainingset including images and labels
	valid	Validationsset including images and labels
	data.yaml	Configurationfile
YOLOtrain	.idea	Programfile
	runs	Results and Diagrams from Training, Validation and Testing
	TUDataset	Copy of the TUDataset
	data.yaml	Configurationfile
	README.dataset	
	README.roboflow	
	main.py	Python Programfile
	yolov8m.pt	Pretrained Yolov8m model
	yolov8s.pt	Pretrained Yolov8s model
Images		Images included in Diplomathesis
Figures		Figures included in Diplomathesis
Excel	Digitales VZ	Overview of Task sheets
	Stat. Anal. Research	Statistical Analysis of Research Field
	Thesaurus File	Thesaurus File for Stat. Analysis
	SLR Research	Pubications included in SLR on "Succesfully implemented projects in Research"
	SLR Practice	Pubications included in SLR on "Succesfully implemented projects in Practice"
	SLR ML in CE	Publications included in SLR on "Machine Learning in AEC"
	SLR ML for Reuse	Publications included in SLR on "Machine Learning for Component Reuse"
	Reuse Market Analysis	Analysis of reusable component markets
	Object Detection Models	Analysis of object detection models for ERP image processing
	Datasets	Compilation of 360 datasets
	Runs	Documentation of Hyperparameter Settings during Training
	Model Assessment	Performance Parameters of Training Configurations
Citavi-File		
DA_EnablingComponentReUse-graphs.pptx		

ANNEX I RELEVANCE OF THEME

Table 51 Preliminary Search in Scopus

Date	Search String	Results
20.05.2023	TITLE(ai OR "artificial intelligence" OR "machine learning" OR "deep learning" OR "object detection" OR "object recognition" OR "computer vision") AND TITLE("component reuse" OR "urban mining" OR "circular economy")	35
20.05.2023	TITLE(ai OR "artificial intelligence" OR "machine learning" OR "deep learning" OR "object detection" OR "object recognition" OR "computer vision") AND TITLE("360 imag*" OR "omnidirectional imag*" OR "panoram*" OR "360°" OR "360 vision" OR "omnidirectional vision" OR "panoram* vision") AND (LIMIT-TO (SUBJAREA,"COMP") OR LIMIT-TO (SUBJAREA,"ENGI"))	118
20.05.2023	TITLE("component reuse" OR "urban mining" OR "circular economy") AND TITLE("360 imag*" OR "omnidirectional imag*" OR "360°" OR "360 vision" OR "omnidirectional vision" OR "panoram* vision")	0
20.05.2023	TITLE(ai OR "artificial intelligence" OR "machine learning" OR "deep learning" OR "object detection" OR "object recognition" OR "computer vision") AND TITLE("360 imag*" OR "omnidirectional imag*" OR "panoram*" OR "360°" OR "360 vision" OR "omnidirectional vision" OR "panoram* vision") AND TITLE("component reuse" OR "urban mining" OR "circular economy")	0
20.05.2023	TITLE-ABS-KEY (ai OR "artificial intelligence" OR "machine learning" OR "deep learning" OR "object detection" OR "object recognition" OR "computer vision")	0

AND TITLE-ABS-KEY ("360 imag*" OR "omnidirectional imag*" OR "panoram*" OR "360°" OR "360 vision" OR "omnidirectional vision" OR "panoram* vision")

AND TITLE-ABS-KEY ("component reuse" OR "urban mining" OR "circular economy")

Table 52 Preliminary Search in Web of Science

Date	Searchstring	Re-sults
20.05.2023	TI= (ai OR "artificial intelligence" OR "machine learning" OR "deep learning" OR "object detection" OR "object recognition" OR "computer vision") AND TI=("component reuse" OR "urban mining" OR "circular economy")	31
20.05.2023	TI=(ai OR "artificial intelligence" OR "machine learning" OR "deep learning" OR "object detection" OR "object recognition" OR "computer vision") AND TI=("360 imag*" OR "omnidirectional imag*" OR "panoram*" OR "360°" OR "360 vision" OR "omnidirectional vision" OR "panoram* vision") and limit to: Computer Science, Engineering	74
20.05.2023	TI=("component reuse" OR "urban mining" OR "circular econ-omy") AND TI=("360 imag*" OR "omnidirectional imag*" OR "360°" OR "360 vision" OR "omnidirectional vision" OR "panoram* vision")	0
20.05.2023	TI=(ai OR "artificial intelligence" OR "machine learning" OR "deep learning" OR "object detection" OR "object recognition" OR "computer vision") AND TI=("360 imag*" OR "omnidirectional imag*" OR "panoram*" OR "360°" OR "360 vision" OR "omnidirectional vision" OR "panoram* vision") AND TI=("component reuse" OR "urban mining" OR "circular economy")	0

ANNEX II RESEARCH PROTOCOL

SUCCESSFULLY IMPLEMENTED PROJECTS IN RESEARCH

Table 53 Overview of research results in Scopus, Google Scholar and Web of Science

	Scopus	Google Scholar	Web of Science
Search String	*TITLE (circular AND economy) AND TITLE (built AND environment) OR TITLE (construction) OR TITLE (building) OR TITLE (aec)*	*allintitle: "built environment" OR aec OR building OR construction "circular economy" "*	*TI=("circular economy") AND TI=("built environment" OR aec OR construction OR building)*
Date of Search	24.01.2023	20.01.2023	19.01.2023
Number of results	366	916	281
Filters	*AND (LIMIT-TO (OA,"all") OR LIMIT-TO (OA,"publisherfullgold") OR LIMIT-TO (OA,"publisherhybridgold") OR LIMIT-TO (OA,"publisherfree2read") OR LIMIT-TO (OA,"repository")) AND (LIMIT-TO (DOCTYPE,"re"))*	*Review Articles*	*OpenAccess, Review Articles*
Number of results	28	99	24
Selected reviews	11	27	10
Total (elimination acc. to criteria)			**28**

Table 54 Publications included in the SLR on "Successfully implemented projects in research"

Authors	Title	Year	Journal
Yu Y., Junjan V., Yazan D.M., Iacob M.-E.	A systematic literature review on Circular Economy implementation in the construction industry: a policy-making perspective	2022	Resour. Conserv. Recycl.
Sáez-de-Guinoa A., Zambrana-Vasquez D., Fernández V., Bartolomé C.	Circular Economy in the European Construction Sector: A Review of Strategies for Implementation in Building Renovation	2022	
Andersen S.C., Birgisdottir H., Birkved M.	Life Cycle Assessments of Circular Economy in the Built Environment—A Scoping Review	2022	Sustainability
Yu Y., Yazan D.M., Junjan V., Iacob M.-E.	Circular economy in the construction industry: A review of decision support tools based on Information & Communication Technologies	2022	Journal of Cleaner Production
Osobajo O.A., Oke A., Omotayo T., Obi L.I.	A systematic review of circular economy research in the construction industry	2022	Smart Sustain. Built Environ.
Purchase C.K., Al Zulayq D.M., O'brien B.T., Kowalewski M.J., Berenjian A., Tarighaleslami A.H., Seifan M.	Circular economy of construction and demolition waste: A literature review on lessons, challenges, and benefits	2022	Materials
Charef R., Morel J.-C., Rakhshan K.	Barriers to implementing the circular economy in the construction industry: A critical review	2021	Sustainability
Akhimien N.G., Latif E., Hou S.S.	Application of circular economy principles in buildings: A systematic review	2021	J. Build. Eng.
Ginga C.P., Ongpeng J.M.C., Daly M.K.M.	Circular economy on construction and demolition waste: A literature review on material recovery and production	2020	Mater.
Gallego-Schmid A., Chen H.-M., Sharmina M., Mendoza J.M.F.	Links between circular economy and climate change mitigation in the built environment	2020	Journal of Cleaner Production
Anastasiades K., Blom J., Buyle M., Audenaert A.	Translating the circular economy to bridge construction: Lessons learnt from a critical literature review	2020	Renewable Sustainable Energy Rev
Joensuu, Tuomo; Edelman, Harry; Saari, Arto;	Circular economy practices in the built environment	2020	Journal of cleaner production
Munaro, Mayara Regina; Tavares, Sérgio Fernando; Bragança, Luís;	Towards circular and more sustainable buildings: A systematic literature review on the circular economy in the built environment	2020	Journal of Cleaner Production
Çimen, Ömer;	Construction and built environment in circular economy: A comprehensive literature review	2021	Journal of cleaner production
Mhatre, Purva; Gedam, Vidyadhar; Unnikrishnan, Seema; Verma, Sanjeev;	Circular economy in built environment–Literature review and theory development	2021	Journal of building engineering

Oluleye, Benjamin I; Chan, Daniel WM; Olawumi, Timothy O;	Barriers to circular economy adoption and concomitant implementation strategies in building construction and demolition waste management: A PRISMA and interpretive structural modeling approach	2022	Habitat International
Tirado, Rafaela; Aublet, Adélaïde; Laurenceau, Sylvain; Habert, Guillaume;	Challenges and opportunities for circular economy promotion in the building sector	2022	Sustainability
Benachio, Gabriel Luiz Fritz; Freitas, Maria do Carmo Duarte; Tavares, Sergio Fernando;	Circular economy in the construction industry: A systematic literature review	2020	Journal of cleaner production
Hossain, Md Uzzal; Ng, S Thomas; Antwi-Afari, Prince; Amor, Ben;	Circular economy and the construction industry: Existing trends, challenges and prospective framework for sustainable construction	2020	Renewable and Sustainable Energy Reviews
Ruiz, Luis Alberto López; Ramón, Xavier Roca; Domingo, Santiago Gassó;	The circular economy in the construction and demolition waste sector–A review and an integrative model approach	2020	Journal of Cleaner Production
Ghisellini, Patrizia; Ripa, Maddalena; Ulgiati, Sergio;	Exploring environmental and economic costs and benefits of a circular economy approach to the construction and demolition sector. A literature review	2018	Journal of Cleaner Production
Wuni, Ibrahim Yahaya;	Mapping the barriers to circular economy adoption in the construction industry: A systematic review, Pareto analysis, and mitigation strategy map	2022	Building and Environment
Charef, Rabia; Lu, Weisheng; Hall, Daniel;	The transition to the circular economy of the construction industry: Insights into sustainable approaches to improve the understanding	2022	Journal of Cleaner Production
Osei-Tutu, Safowaa; Ayarkwa, Joshua; Osei-Asibey, Dickson; Nani, Gabriel; Afful, Aba Essanowa;	Barriers impeding circular economy (CE) uptake in the construction industry	2022	Smart and Sustainable Built Environment
Wuni, Ibrahim Yahaya;	A systematic review of the critical success factors for implementing circular economy in construction projects	2022	Sustainable Development
Norouzi, Masoud; Chàfer, Marta; Cabeza, Luisa F; Jiménez, Laureano; Boer, Dieter;	Circular economy in the building and construction sector: A scientific evolution analysis	2021	Journal of Building Engineering
Adams, Katherine Tebbatt; Osmani, Mohamed; Thorpe, Tony; Thornback, Jane;	Circular economy in construction: current awareness, challenges and enablers	2017	Proceedings of the Institution of Civil Engineers-Waste and Resource Management

SUCCESSFULLY IMPLEMENTED PROJECTS IN PRACTICE

Table 55 Overview of research results in Scopus, Google Scholar and Web of Science

	Scopus	Google Scholar	Web of Science	Search-Engine	Magazines
Search String	*TITLE (circular AND economy) AND TITLE (built AND environment) OR TITLE (construction) OR TITLE (building) OR TITLE (aec) AND TITLE-ABS-KEY ("case study") OR TITLE-ABS-KEY ("project")*	allintitle: "circular economy" "case study" "building" OR "built environment" OR "construction" OR "aec"	*TI=("circular economy") AND TI=("built environment" OR aec OR construction OR building) and TI= ("case study" OR "project")*	*Google SLUB (Availability)*	*DETAIL Kreislaufwirtscaft*
Date of Search	22.02.2023	22.02.2023	22.02.2023		
Number of results	138	99	20		
Filters			*OpenAccess, Review Articles*		
Number of results	73	67	65		
Selected results	17	7	2		
Total (elimination acc. to criteria)					**26**

Table 56 Publications included in SRL on "Succesfully implemented projects"

Authors	Title	Year	Journal
Christensen T.B., Johansen M.R., Buchard M.V., Glarborg C.N.	Closing the material loops for construction and demolition waste: The circular economy on the island Bornholm, Denmark	2022	Resources, Conservation and Recycling Advances
Maury-Ramírez A., Illera-Perozo D., Mesa J.A.	Circular Economy in the Construction Sector: A Case Study of Santiago de Cali (Colombia)	2022	Sustainability (Switzerland)
O'Grady T.M., Minunno R., Chong H.-Y., Morrison G.M.	Interconnections: An analysis of disassemblable building connection systems towards a circular economy	2021	Buildings
Dey S., Iulo L.D.	The Circular Economy of Dharavi: Making building materials from waste	2021	Enquiry
Cellucci C.	Circular economy strategies for adaptive reuse of residential building	2021	Vitruvio
Hjaltadóttir R.E., Hild P.	Circular Economy in the building industry European policy and local practices	2021	European Planning Studies
Zabek M., Wirth M., Hildebrand L.	Evaluating Regional Strategies towards a Circular Economy in the Built Environment	2020	IOP Conference Series: Earth and Environmental Science
Ajayebi A., Hopkinson P., Zhou K., Lam D., Chen H.-M., Wang Y.	Spatiotemporal model to quantify stocks of building structural products for a prospective circular economy	2020	Resources, Conservation and Recycling
Pearlmutter D., Theochari D., Nehls T., Pinho P., Piro P., Korolova A., Papaefthimiou S., Mateo M.C.G., Calheiros C., Zluwa I., Pitha U., Schosseler P., Florentin Y., Ouannou S., Gal E., Aicher A., Arnold K., Igondová E., Pucher B.	Enhancing the circular economy with nature-based solutions in the built urban environment: Green building materials, systems and sites	2020	Blue-Green Systems
Huovila P., Iyer-Raniga U., Maity S.	Circular Economy in the Built Environment: Supporting Emerging Concepts	2019	IOP Conference Series: Earth and Environmental Science
Akanbi L.A., Oyedele L.O., Omoteso K., Bilal M., Akinade O.O., Ajayi A.O., Davila Delgado J.M., Owolabi H.A.	Disassembly and deconstruction analytics system (D-DAS) for construction in a circular economy	2019	Journal of Cleaner Production
Ajayabi A., Chen H.-M., Zhou K., Hopkinson P., Wang Y., Lam D.	REBUILD: Regenerative Buildings and Construction systems for a Circular Economy	2019	IOP Conference Series: Earth and Environmental Science

Leising E., Quist J., Bocken N.	Circular Economy in the building sector: Three cases and a collaboration tool	2018	Journal of Cleaner Production
Akanbi L.A., Oyedele L.O., Akinade O.O., Ajayi A.O., Davila Delgado M., Bilal M., Bello S.A.	Salvaging building materials in a circular economy: A BIM-based whole-life performance estimator	2018	Resources, Conservation and Recycling
Cross M.	Wallasea Island Wild Coast Project, UK: Circular economy in the built environment	2017	Proceedings of Institution of Civil Engineers: Waste and Resource Management
Andersen, SC; Birgisdottir, H; Birkved, M	Life Cycle Assessments of Circular Economy in the Built Environment-A Scoping Review	2022	SUSTAINABILITY
Rakhshan, K; Morel, JC; Daneshkhah, A	Predicting the technical reusability of load-bearing building components: A probabilistic approach towards developing a Circular Economy framework	2021	JOURNAL OF BUILDING ENGINEERING
Bertino, G; Kisser, J; Zeilinger, J; Langergraber, G; Fischer, T; Osterreicher, D	Fundamentals of Building Deconstruction as a Circular Economy Strategy for the Reuse of Construction Materials	2021	APPLIED SCIENCES-BASEL
Mangialardo, Alessia; Micelli, Ezio;	Rethinking the construction industry under the circular economy: principles and case studies	2018	Smart and Sustainable Planning for Cities and Regions: Results of SSPCR 2017 2
Stallkamp, Christoph;	https://www.crl.fraunhofer.de/selfcheck/	2021	links
Mangialardo, A; Micelli E (2018b)	Rethinking the construction industry under the circular economy: principles and case studies		Smart and sustainable planning for cities and regions. Springer, Cham, Switzerland
Engez, Anil; Ranta, Valtteri; Aarikka-Stenroos, Leena;	How innovations catalyse the circular economy: building a map of circular economy innovation types from a multiple-case study	2021	Research Handbook of Innovation for a Circular Economy
Weinstein, Zvi;	Circular Economy in Construction from Waste to Green Recycled Products in Israel: A Case Study	2021	Rethinking Sustainability Towards a Regenerative Economy
Çetin, Sultan; Gruis, Vincent; Straub, Ad;	Digitalization for a Circular Economy in the Building Industry: Multiple-Case Study of Dutch Housing Organizations		Available at SSRN 4114994

ML AS AN ENABLER OF CE IN AEC

Table 57 Research protocol for machine learning applications in the BE and for CE

	Scopus	Web of Science
Machine Learning + Circular Economy + Built Environment		
Search String	*TITLE ("circular economy" OR reuse OR "urban mining") AND TITLE-ABS-KEY(ai OR "artificial intelligence" OR "machine learning" OR "deep learning") AND TITLE-ABS-KEY(construction OR building OR "built environment") AND (LIMIT-TO (OA,"all") OR LIMIT-TO (OA,"publisherfullgold") OR LIMIT-TO (OA,"publisherfree2read") OR LIMIT-TO (OA,"repository"))*	*TI=("circular economy" OR "reuse" or "urban mining") AND TI = ("built environment" OR construction OR building OR aec) AND (TI=("artificial intelligence" OR ai OR "machine learning" OR "deep learning" OR "neural networks") OR AB =("artificial intelligence" OR ai OR "machine learning" OR "deep learning" OR "neural networks"))*
Date of Search	01.03.2023	01.03.2023
Results	19	10
Relevant results	8	1
Machine Learning + Built Environment		
Filters	*TITLE(ai OR "artificial intelligence" OR "machine learning" OR "deep learning") AND TITLE(construction OR "built environment" OR "building industry") AND (LIMIT-TO (OA,"all") OR LIMIT-TO (OA,"publisherfullgold") OR LIMIT-TO (OA,"publisherfree2read") OR LIMIT-TO (OA,"repository")) AND (LIMIT-TO (SUBJAREA,"ENGI") OR LIMIT-TO (SUBJAREA,"ENVI") OR LIMIT-TO (SUBJAREA,"MATE"))*	TI = ("built environment" OR "construction industry" OR "building industry" OR aec) AND TI=("artificial intelligence" OR ai OR "machine learning" OR "deep learning" OR "neural networks")
Results	240	28
Relevant results	-	7
Machine Learning + Circular Economy		
Search query	TITLE ("circular economy" OR reuse OR "urban mining") AND TITLE(ai OR "artificial intelligence" OR "machine learning" OR "deep learning") AND (LIMIT-TO (OA,"all") OR LIMIT-TO (OA,"publisherfullgold") OR LIMIT-TO (OA,"publisherhybridgold") OR LIMIT-TO (OA,"publisherfree2read") OR LIMIT-TO (OA,"repository")	*TI=("circular economy" OR "reuse" or "urban mining") AND TI=("artificial intelligence" OR ai OR "machine learning" OR "deep learning" OR "neural networks")*
Results	17	78
Relevant results	2	11
Total (elimination acc. to criteria)		**26**
Manually added from Google Scholar		**1**

Table 58 Publications included in the review "Machine Learning for Component Reuse"

Authors	***Title***	***Year***	***Journal***
Duan Q., Qi L., Cao R., Si P.	*Research on Sustainable Reuse of Urban Ruins Based on Artificial Intelligence Technology: A Study of Guangzhou*	*2022*	*Sustainability*
Rakhshan K., Morel J.-C., Daneshkhah A.	*Predicting the **technical** reusability of load-bearing building components: A probabilistic approach towards developing a Circular Economy framework*	*2021*	*Journal of Building Engineering*
Rakhshan K., Morel J.-C., Daneshkhah A.	*A probabilistic predictive model for assessing the **economic** reusability of load-bearing building components: Developing a Circular Economy framework*	*2021*	*Sustinable Production and Consumption*
Lai, Y; Kontokosta, CE	*Topic modeling to discover the thematic structure and spatial-temporal patterns of building renovation and adaptive reuse in cities*	*2019*	*Computers, Environment and Urban systems*
Daware, S; Chandel, S; Rai, B	*A machine learning framework for urban mining: A case study on recovery of copper from printed circuit boards*	*2022*	*Minerals Engineering*
Yu, KH; Zhang, Y; Li, DN; Montenegro-Marin, CE; Kumar, PM	*Environmental planning based on reduce, reuse, recycle and recover using artificial intelligence*	*2021*	*Environmental Impact Assessment Review*
Genske, DD; Huang, DB; Ruff, A	*An Assessment Tool for Land Reuse with Artificial Intelligence Method*	*2010*	*International Journal of Automation and Computing*
Yeung, Jamie; Walbridge, Scott; Haas, Carl	*The role of geometric characterization in supporting structural steel reuse decisions*	*2015*	*Resources, Conservation and Recycling*
Fujita, Masanori; Kuki, Keiichi	*An Evaluation of Mechanical Properties with the Hardness of Building Steel Structural Members for Reuse by NDT*	*2016*	*Metals*
Cavalli, Alberto; Bevilacqua, Lorella; Capecchi, Gianluca; Cibecchini, Daniele; Fioravanti, Marco; Goli, Giacomo; Togni, Marco; Uzielli, Luca	*MOE and MOR assessment of in service and dismantled old structural timber*	*2016*	*Engineering Strcutures*
Çetin, S., De Wolf, C., Bocken, N.,"57222071860	*Circular digital built environment: An emerging framework*	*2021*	*Sustainability*
Darko, A., Chan, A.P.C., Adabre, M.A., Edwards, D.J., Hosseini, M.R., Ameyaw, E.E.,"57190178235	*Artificial intelligence in the AEC industry: Scientometric analysis and visualization of research activities"*	*2020*	*Automation in Construction*

Table 59 Publications regarding ML application for transitioning CE in the BE according to Çetin et al. (2021)

Authors	Title	Application of ML
Design Decisions		
(Gan et al., 2020)	Simulation optimisation towards energy efficient green buildings: Current status and future trends	
(Arcadis)	Artificial Intelligence in the AEC Industry: A Code of Practice	
(Płoszaj-Mazurek et al., 2020)	Methods to Optimize Carbon Footprint of Buildings in Regenerative Architectural Design with the Use of Machine Learning, Convolutional Neural Network, and Parametric Design	
(Mehmood et al., 2019)	A review of the applications of artificial intelligence and big data to buildings for energy-efficiency and a comfortable indoor living environment	
	FASA Project	
(Akanbi et al., 2020)	Deep learning model for Demolition Waste Prediction in a circular economy	
(Rakhshan et al., 2021a)	A probabilistic predictive model for assessing the economic reusability of load-bearing building components: Developing a Circular Economy framework	This study develops a probabilistic predictive model to evaluate the economic reusability of load-bearing building elements. (Rakhshan et al., 2021a, p. 2)
(Oluleye et al., 2023)	Adopting Artificial Intelligence for enhancing the implementation of systemic circularity in the construction industry: A critical review	
(Davis et al., 2021)	The classification of construction waste material using a deep convolutional neural network	
	Determination of the composition of recycled aggregates using a deep learning-based image analysis	

ANNEX III REUSABILITY ASSESSMENT

Table 60 Questions for analysis of the characteristics that have direct influence (adapted from (Carvalho Machado et al., 2018, p. 10)

Characteristics	Definition	Questions for Analysis	Yes	No
Expected durability	Construction materials resulting from deconstruction should have a remaining lifecycle that is equal to or longer than the desired lifecycle of a new component to avoid financial and environmental losses and minimize waste generation.	Is the expected durability of the component meant for reutilization longer than or equal to the lifecycle desired from the new use?	+	x
Toxicity and construction material hazardousness	In DfD toxic and hazardous construction materials should be avoided to reduce contamination potential and health risks to workers. If the usage of these materials is inevitable, the design should consider the possibility of an easy and safe removal.	Are toxic or hazardous construction materials used?	*	+
		If toxic or hazardous construction materials are used, is it possible to safely and easily remove them?	−	x
Possibility of reutilizing (or preferably re-using) construction materials	When building materials can be reused for their original purpose with minimal repairs, it justifies the deconstruction process. This end-of-life scenario is the most effective way to minimize environmental impacts during a building's lifespan since it doesn't involve reprocessing.	Can the construction material be reutilized in any way?	+	x
		Is the deconstruction process necessary to reutilize the construction material?	+	x
Damage caused to connected parts during construction	DfD guidelines generally suggest using mechanical connections instead of chemical ones as most chemical connections damage the connected parts during dismantling. However, it's important to analyze Guideline 3.2, which recommends using mechanical connections, in terms of the possibility of reusing connections after deconstruction and possible damage to the connected parts. Some chemical connections may not cause damage during deconstruction. If the damage caused during the process is difficult to repair, deconstruction may not be a viable option.	Will the connection type cause any kind of damage to connected parts during deconstruction?	*	+
		Can any damage arising from deconstruction be repaired?	−	x
Damage to connections	Ideally, connections should remain intact during deconstruction. It's crucial to assess if the	Will connections be damaged during deconstruction?	*	+

during the process	connection is necessary, easily repairable, or replaceable to ensure reuse without compromising deconstruction viability. Otherwise, damage to the connection will hinder the possibility of reuse.	Are connections necessary in the new use?	*	–
		Can connections be repaired or replaced when construction materials are reutilized?	–	x
Construction material separation	The separation of construction materials is important for facilitating the reuse of components according to DfD guidelines, which are based on layer theory. This theory divides a building into layers based on different lifecycles of elements, with faster replacement cycles located closer to the surface. The ease of separating a reusable component from the rest of the building should be considered during deconstruction. Furthermore, the importance of reusing construction materials by focusing on their separation when they cannot be reused as a group is emphasized. However, there may be cases where separation is impossible without causing damage to the materials and preventing reutilization.	Is it possible to separate the construction materials meant for reutilization?	+	*
		If separation is impossible, can construction materials be reutilized as a group without environmental damage?	–	x
Space for equipment and manoeuvring	To ensure safe and efficient deconstruction, the layout of the deconstruction zone, building shape, and size of equipment and machinery must be considered. It is important to control the built environment and space around the building to ensure access for necessary equipment and manoeuvring. In some cases, it may be impossible to access the necessary equipment, which could compromise the safety of the operation and the integrity of construction materials.	Is the space around the building sufficient to ensure access and manoeuvring room for equipment and machinery, considering the volume of construction materials that will be removed?	+	x
Space for correct storage of construction materials	The closer the storage space to where deconstruction or re-sale is taking place, the lower the environmental impact and transportation costs. The location must not affect urban areas and it must be a safe environment. It is necessary to evaluate whether the space and storage method are adequate for the construction materials, or whether damage may be caused, compromising reutilization	Is there an adequate storage space that can ensure that stored construction materials will not deteriorate?	+	x
Risk assessment and adoption of security measures	Prioritize risk reduction in building dismantling to protect workers, nearby individuals, and construction materials. Identify risks, implement control measures, and train the work team.	Can risks present in the deconstruction process be eliminated or controlled, allowing procedures to be carried out safely?	+	x

Disassembly procedure	A basic deconstruction plan must be provided that include considerations of and recommendations for the deconstruction procedure, and in particular, the order of disassembly, ideal element and component removal techniques, the location of construction materials that will be reutilized, lifting points, an equipment list, the tools and machinery that will be necessary, and a safety plan, among other aspects.	Is there a deconstruction procedure with a disassembly order; an ideal technique for removing components and elements; locations of construction materials to be removed; lifting points; and a list of equipment, tools and machinery necessary and the safety plan?	+	x
		Have deconstruction procedures, including the safety plan, been passed on to those involved in the process, raising the team's awareness?	+	x
As-built drawings	As-built drawings help with identifying parts and developing safe disassembly procedures, but an architectural/structural design update may be needed if they are non-existent or insufficiently updated. Building Information Modelling (BIM) can facilitate information management and data exchange for effective deconstruction, and accurate and complete information should be stored in a BIM-based building model.	Are there an updated as-built drawings of the building that will be deconstructed?	+	*
		Is there an architectural/structural design update, according to the building?	−	x
DfD strategies adopted at the design stage	Disassembling the building will be more viable if DfD strategies are incorporated at the project's design stage. This characteristic involves possible strategies that can be adopted at the beginning of construction in order to enable future deconstruction. Even when a building has not been designed for deconstruction, certain basic characteristics that favour deconstruction must be present to enable the process, as well as characteristics that are related to the selection of construction materials and the connections between them.	The characteristics listed in this Table 3 are considered under ideal or acceptable conditions?	+	*
		Are there actions which could be taken after construction to change the characteristics' condition and make the deconstruction viable?	-	x
Legend	+ Ideal condition-positive aspect;	x Condition that can impede deconstruction;		
	− Acceptable condition-negative aspect;	* The analysis of deconstruction viability depends on the next quesit		

ANNEX IV OBJECT DETECTION MODELS

Table 61 Machine Learning Frameworks for Object Detection using 360° images

R-CNN	Two-stage	planar	AlexNet, VGG, ResNet, Inception etc.	Yes	Bounding Box	PASCAL VOC 2010; ILSVRC2013		53.7% (Pascal VOC); 31.4% (ILSVRC2013)	Moderate to High	[Girshick et al., 2014]
SPPNet	Two-stage	planar	VGG16	No	Bounding Box	ImageNet; Pascal VOC 2007; Caltech101		59.2%	Moderate	[He et al., 2015]
Fast R-CNN	Two-stage	planar	VGG16, ResNet-101	Yes	Bounding Box	PASCAL VOC 2012		66% (PASCAL VOC2012)	Moderate	[Girshick, 2015]
Faster R-CNN	Two-stage	planar	VGG16, ResNet, Inception, AlexNet	No	Bounding Box	PASCAL VOC 2007, 2012, MS COCO	30 0	78.8 (VOC2007) ;75.9% (VOC2012); 42.7% (COCO)	High	[Ren et al., 2015]
RFCN	Two-stage	planar	ResNet-101	Yes (600x1000)	Bounding Box	PASCAL VOC2007		73.6% (Pascal VOC)	High	[Dai et al., 2016]
Mask RCNN	Two-stage	planar	ResNet-101, ResNeXt-101, etc.	No, Training (800x800)	Instance Segmentation Mask	COCO 2015; COCO 2016		62.3% (COCO)	High	[He et al., 2017]
Cascade RCNN	Two-stage	planar	ResNet-50, ResNet-101	Yes (800 x 1333)	Bounding Box	PASCAL VOC2007, VOC2012		79.6% (Pascal VOC2007)	High	[Cai and Vasconcelos, 2018; Cai et al., 2018]
Light Head RCNN	Two-stage	planar	ResNet, ResNeXt	Yes (600x1000; 800x1200)	Bounding Box	COCO		41.5% (COCO test-dev)	Moderate	[Li et al., 2018]
Sphere SSD (based on SphereNet)	Two-stage	spherical	SphereNet; VGG16	Yes (512× 256)	Spherical BB	Flying Cars	-	50.18% (Flying Cars)	Moderate to High	[Coors et al., 2018]
Reprojection R-CNN (Rep R-CNN)	Two-stage	spherical	VGG16	Yes	Spherical BB	VOC360, COCO-Men (synthetic datasets); SUN360		71.88% (VOC360); 81.48 (COCO-Men)	High	[Zhao, You et al., 2019]
YOLO	unified	planar	Darknet-19, Darknet-53	Yes (in multiples of 32)	Bounding Box	PASCAL VOC2007, VOC2012		63.4% (VOC2007; VOC2012)	Moderate to High	[Redmon et al. 2016]
OverFeat	unified	planar	AlexNet, OverFeat	Yes	Bounding Box	ImageNet 2012	-	24.3 (ILSVRC13 test set)	Moderate to High	[Sermanet et al. 2014]
SSD (Single Shot MultiBox Detector)	unified	planar	VGG16, MobileNet, ResNet50, ResNet101	Yes (300×300; 512x512)	Bounding Box	PASCAL VOC2007, COCO, ILSVRC	-	74.3% (VOC2007; 300x300); 76.9% (VOC2007; 512 x 512)	Moderate	[Liu et al., 2016]
RetinaNet	unified	planar	ResNet-101-FPN	Yes	Bounding Box	COCO trainval35k		40.8% (COCO)	High	[Lin, Goyal et al., 2017]
Deng et al.	unified	planar	VGG16	No	Bounding Box	Own dataset		68.7%	Moderate to High	[Deng, Zhu et al., 2017]
RepF-Net	unified	spherical	StdConv; DeformConv; SteConv;	Yes (640 x 640)	Bounding Box	RepF-dataset		80.0%	High	[Li, Meng et al., 2023]
Panoramic BlitzNet	unified	spherical	ResNet50	No	Spherical BB	Own dataset generated from SUN360		77.8% (on complete SUN360)	Moderate	[Guerrero-Viu, Fernandez-Labrador et al., 2020]
Multi-projection YOLO (mp-YOLO)	unified	spherical	Darknet-19, Darknet-53	Yes (864 x 864; 608 x 608)	Bounding Box	ImageNet, COCO		34.29%	Moderate	[Yang, Qian et al., 2018]
CornerNet	unified	planar	Hourglass-104	No	Keypoints	COCO	-	42.2% (COCO)	Moderate	[Law and Deng 2018]