
Use of Artificial Intelligence in Construction

Master's Thesis

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from

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Conceptual Formulation

Master Thesis for Mr Mohanad Ali

Student number S0581312

Topic:

Use of Artificial Intelligence in Construction

Background

In the construction business, recent decades have seen the fast development of digital technology and the proliferation of big data. AI implementation, in particular, which aims to imbue robots with human-like intelligent behavior and thinking, has received a lot of attention. Artificial Intelligence (AI) is streamlining operations, boosting productivity, and cutting costs. In the design, planning, scheduling, and monitoring phases of construction, AI is being employed as well. Construction stakeholders can improve project outcomes overall and create more accurate predictions using artificial intelligence (AI). Construction stakeholders are now able to work smarter, quicker, and more effectively thanks to technology, which ultimately leads to better outcomes and higher client satisfaction.

The study will analyze the technologies of AI and the aspects of the construction industry. Then, an analysis will be made for the current usages of AI technologies in construction. The final goal of the study will be to define the current usages of AI in construction and to predict the future ones. Furthermore, the study will indicate the benefits, limitations, challenges and drawbacks of using AI in construction.

Research Objectives

- Study the possible interactions between Artificial Intelligence technologies and construction activities.
- Explain the current usages of Artificial Intelligence in the construction industry.
- Predict the future usages of Artificial Intelligence in the construction industry.

Methodology

- Literature review on Artificial Intelligence technologies.
- Forming a summary and conclusions of the currently used technologies.

Research Questions

- What is artificial intelligence?
- What are the aspects of construction?
- How can Artificial intelligence be used in construction projects?
- How can Artificial intelligence support project managers?
- What are the benefits of using Artificial Intelligence compared to traditional project management?
- What are the limitations and challenges of using Artificial Intelligence in construction?

Signature of the 1st Supervisor

Signature of the 2nd Supervisor

Abstract

Artificial Intelligence (AI) has been involved in the construction industry research since 1974, and it has gained exponential growth in research interest starting in the 21st century. Artificial Intelligence is divided into many branches, such as Machine Learning (ML), Artificial Neural Networks (ANN), Deep Learning (DL), Knowledge-Based Systems (KBSes), Computer Vision (CV) and Image Recognition, Natural Language Processing (NLP), Internet of Things (IoT) and Robotics. Applications of the mentioned AI branches in the construction industry are discussed here, along with the challenges for their implementation. Moreover, five case studies discuss the involvement of different AI technologies and tools in project cost forecasting, report analysis, machinery activity, safety monitoring systems, construction monitoring and reporting, and remote construction site management.

A literature review is formed to discuss the use of AI in construction. A simplified definition is given for each AI branch addressing the non-AI background readers, with examples given of the possible applications in different industries to provide a complete overview. Applications and challenges of using AI technologies and tools in construction are also discussed and investigated from academic and practical perspectives. Five case studies are explained and discussed to verify the research argument.

Keywords

Artificial Intelligence, Construction Industry, Machine Learning, Knowledge-Based Systems, Computer Vision and Image Recognition, Natural Language Processing, Internet of Things and Robotics

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List of Abbreviations

AEC	Architecture, Engineering and Construction
AES	Autonomous Excavator System
AGVs	Automated Guided Vehicles
AI	Artificial Intelligence
ALG	Application Layer Gateway
AMRs	Autonomous Mobile Robots
ANN	Artificial Neural Networks
API	Application Programming Interface
AR	Augmented reality
BIM	Building Information Modelling
CNN	Convolutional Neural Network
COVID-19	Coronavirus
CPU	Central Processing Unit
CQF	Certificate in Quantitative Finance
CS	Case Study
CS1	Case Study 1
CS2	Case Study 2
CS3	Case Study 3
CS4	Case Study 4
CS5	Case Study 5
CV	Computer Vision
DL	Deep Learning
DNN	Deep Neural Networks
DT	Digital technology

GDP	Gross Domestic Product
GPS	Global Positioning System
GPU-based	Graphic Processing Unit
HCI	Human and Computer Interaction
IAB	Internet Architecture Board
IBM	International Business Machines corporation
IE	Information Engineering
ILO	International Labor Organization
ILSVRC	ImageNet Large-Scale Visual Recognition Challenge
IoT	Internet of Things
IoT-enabled	Internet of Things enabled
IP	Internet Protocol
IR	Information Retrieval
JIT	Just-in-time
KBS	Knowledge-Based System
KBSes	knowledge-Based systems
KNNs	K-Nearest Neighbors
KPIs	key performance indicators
KYC	Know Your Customer
LRs	Linear Regression
MAPE	Mean Absolute Percentage Error
MEC	Ministry of Education platform
ML	Machine Learning
MLB	Major League Baseball
MLP	Multilayer Perceptron
MLP-type	Multilayer Perceptron type

NBs	Naive Bayes
NLP	natural language processing
OEE	Overall Equipment Effectiveness
OEMs	Original Equipment Manufacturers
OSHA	Occupational Safety and Health Administration
PESTLE	Political, Economic, Social, Technological, Legal, Environmental
POS	Part of Speech tagging
PPE	Personal Protective Equipment
QA	Questions Answering
RFID	Radio Frequency Identification
RGB-D	Red Green Blue-Depth
RNA	Ribonucleic Acid
RTInsights	Real Time Business Insights
SARS-CoV-2	Severe Acute Respiratory Syndrome CoronaVirus 2
SLA	Service Level Agreement
SQP	Support Vector Machine
STEM	Science, Technology, Engineering, and Mathematics Education
SVMs	Support Vector Machines
TF-IDF	Term Frequency – Inverse Document Frequency
TUG	Timed Up and Go
TVs	Televisions
U.S.A	United States of America
UAVs	Unmanned Aerial Vehicles
VINNIE	Very Intelligent Neural Network for Insight and Evaluation
VR	Real Database Value
Wi-Fi	Wireless Fidelity

WWW World Wide Web

XAI Explainable AI

1 Introduction

Economic development and competitiveness are integral to the Architecture, Engineering and construction (AEC) industry. According to a World Economic Forum study, over 8% of global gross domestic product (GDP) is derived from construction in developing countries (WEC, 2016). It has been estimated that the international building investment market will reach \$14.8 trillion by 2025, up from \$10.9 trillion in 2017 (McKinsey & Company, 2022).

Following the COVID-19 pandemic, digital technologies have become increasingly important on construction sites (TRAXXEO, 2023). The digitalisation of the construction industry has demonstrated a rise in revenue surpluses and increased opportunities for winning contracts (TRAXXEO, 2023). Changes and revolutions in the industry are changing positions for connoisseurs and leaders. The construction industry has adopted modern technologies in recent years, where the investment in construction technology was estimated to be \$25 billion from 2014 to 2019 (TRAXXEO, 2023).

Digitalization has become widely accepted as a paradigm since it has improved organizational effectiveness and introduced a new component to conventional business models. Digital technology (DT) has dramatically impacted established companies. Faster communication and easier access to information have radically transformed the expertise sectors, including construction. The construction industry is significantly behind in terms of technical improvements, despite the fact that successfully introducing innovative products can boost the overall economy. Companies are expected to integrate Building Information Modeling (BIM), machine learning, 3D printing, robotics, and other digital innovations within three to ten years into their business processes. (Jazzar et al., 2020, p. 1)

Building on the previous facts, studying the emerging role of artificial intelligence as part of the technological revolution (construction 4.0) in the construction industry is crucial. In this chapter, the background, goals and research structure are discussed.

1.1 Background

Artificial intelligence is not a new term in the construction industry. According to (Darko et al., 2020, p. 1), the first publication of artificial intelligence in the AEC (Architecture, Engineering and Construction) industry was published in 1974. In Figure 1, it can be seen how the progress of the AI trend in construction from 1974 to August 2019.

Figure 1 also shows how the 21st century witnessed the rise of researchers interested in integrating AI technology into the construction industry. Moreover, it started to increase exponentially starting from the year 2010 till 2019.

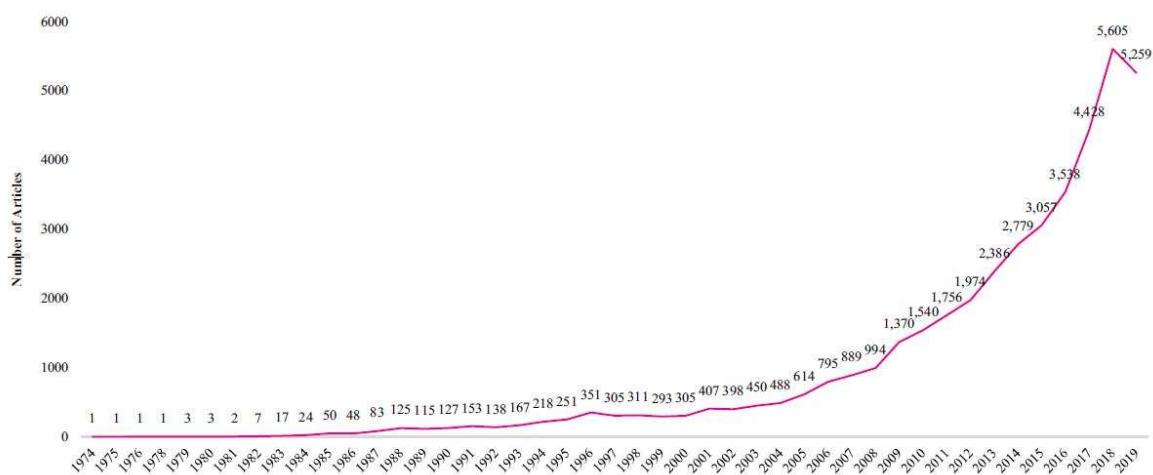


Figure 1 Publications related to AI in AEC from 1974 to August 2019 (Darko et al., 2020, p. 3)

Moreover, Abioye et al. (2021) studied the frequency of publications from 1960 to 2019. The researcher studied technologies such as machine learning (ML), Computer Vision (CV), Natural Language Processing (NLP), Knowledge-Based Systems (KBSes), Robotics and Optimisation. Figure 2 expresses the previously explained relation as a combined graph.

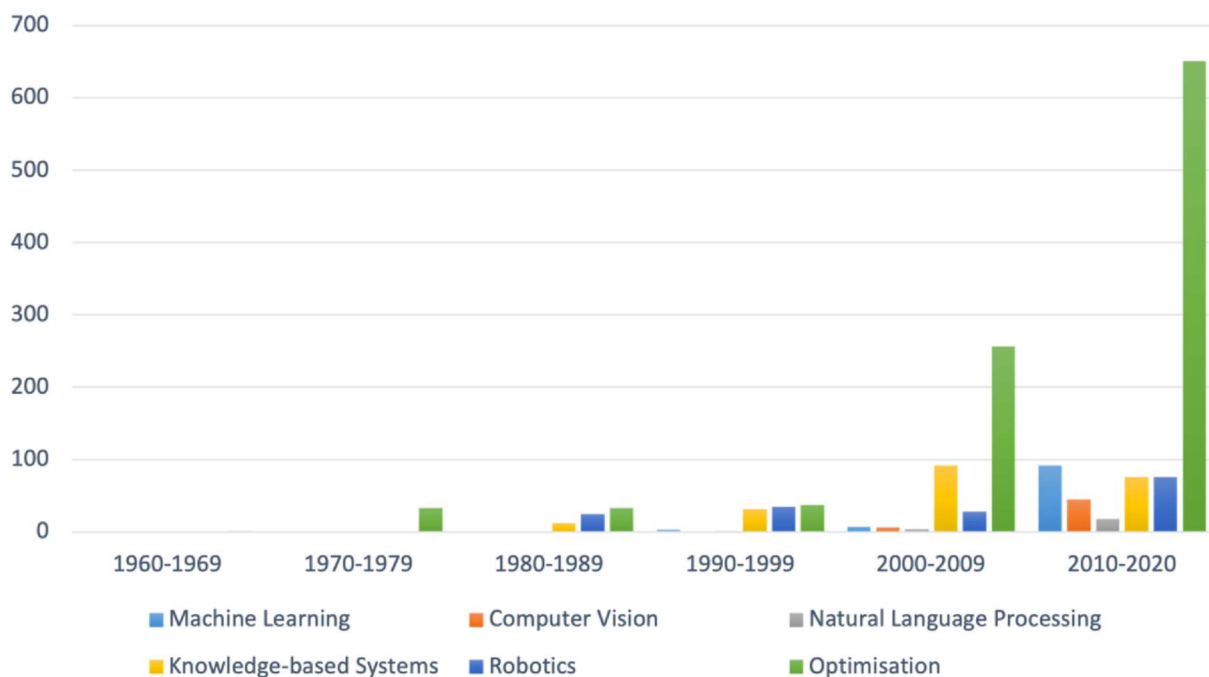


Figure 2 Frequency of papers from 1960 to 2020 (Abioye et al., 2021, p. 5)

Figure 2 shows a significant rise in optimisation in comparison to other technologies. An optimization problem involves finding the best solution based on constraints and deciding how to proceed (Abioye et al., 2021, p. 5). It is predicted that such a technology will be leading by far from others, where the construction projects require is known for its waste in both management and resources. Chapter 2 provides a better understanding of the technologies in detail and includes how those technologies are being used in other industries.

Darko et al. (2020) took a further look at the research interest in artificial intelligence in the construction industry, where the dependency was on the co-occurrence of the keywords which formed the network displayed in Figure 3. A full explanation is provided by Darko et al. (2020, p. 3) about selecting the keywords, the software in use and other criteria for this study. Figure 3 includes the study's technologies and construction aspects intensity; as shown in Figure 3, Optimization is the most studied term. In addition to the expectation of that, both researchers found the same results where now it is a given truth. Neural Networks, Genetic algorithms, machine learning, image processing and data mining are the most commonly used artificial intelligence technologies. The density of the previously mentioned ones is not the same.

On the other hand, from the construction perspective, and based on the most commonly used Artificial intelligence technologies, construction management and

project management are the top terms. Decision-making is a feature which AI can provide to help the AEC industry; As a result, it is also one of the hottest topics in this field. Figure 3 demonstrates that AI and construction are connected in many ways, not only in construction management but also in project development, equipment, design, and life cycle assessment.

The energy topic was also represented, where energy in general, energy efficiency, energy consumption, and thermal comfort were discussed. Moreover, with the rise of the sustainability topic worldwide, it was somehow involved in the construction industry.

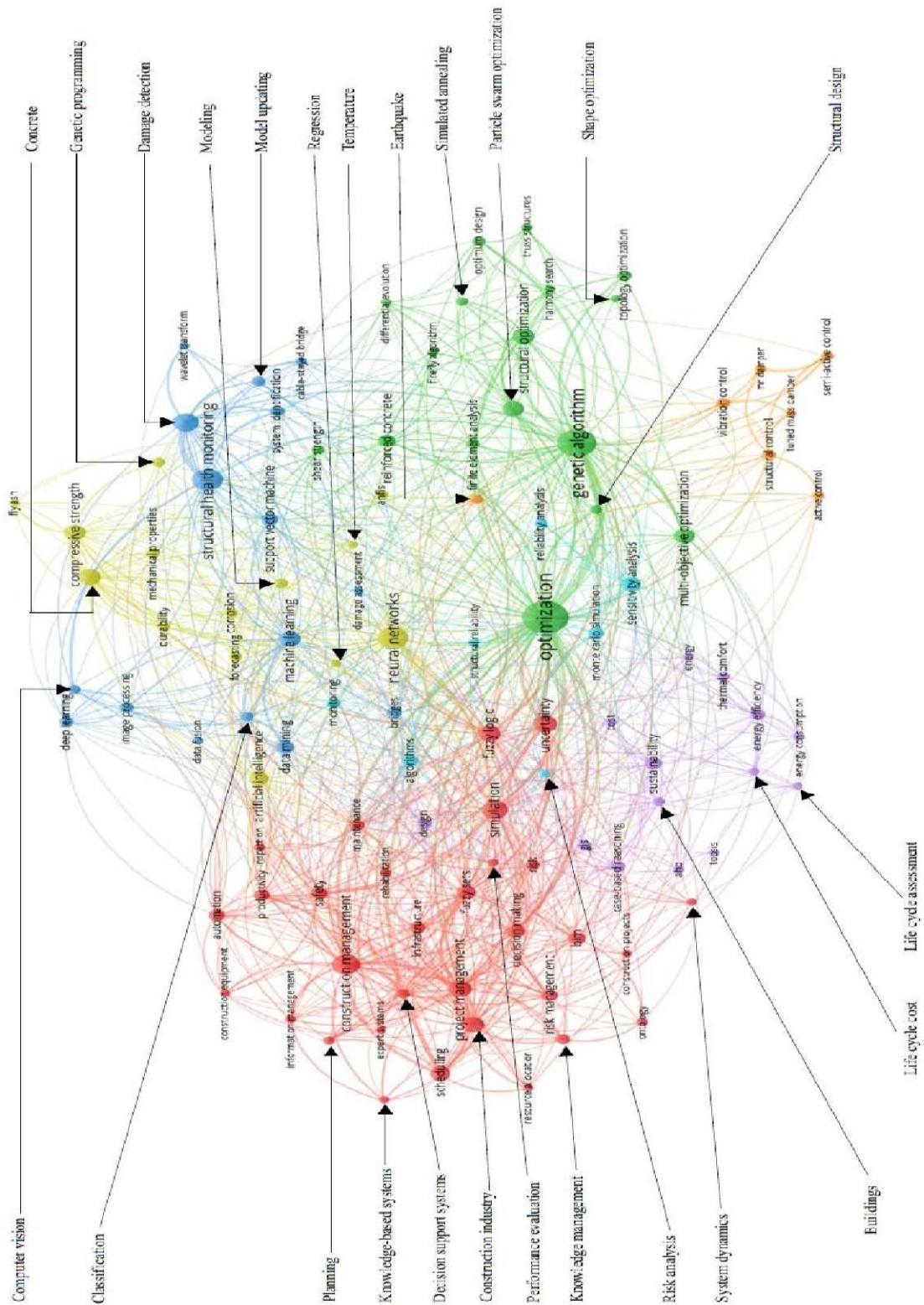


Figure 3 Keyword co-occurrence networks are the main focus of AI-in-the-AECI research.

(Darko et al., 2020, p. 4)

The aim is to learn more about how artificial intelligence is used in the construction industry. In the following, the goals of the research are introduced.

1.2 Goals

This research is formed of four different parts. The first was to prepare a solid background and literature review for the non-specialised AI readers with real explanations from other industries. At the same time, the second one was studying the existing integration of AI in construction, explaining the benefits, risks and applications. The third goal was to define case studies using different AI technologies in different construction industry parts. While the fourth goal was to conclude the research with a straightforward reading approach.

The previously mentioned goals could be summarised as follows:

- Form a literature review about AI.
- Study the possible interactions between Artificial Intelligence technologies and construction activities.
- Explain the current usage of AI in the construction industry using case studies as evidence.
- Predict the future usage of AI in the construction industry.

1.3 Research Structure

The research is structured to achieve the previously mentioned goals and make it easier for the reader to follow the ideas and better understand the topic. Chapter 1 discusses the background of the topic and the relevancy of studies, while the goals are also shown. While Chapter 2 gives the basic knowledge of artificial intelligence and its definition and technologies. The study in this chapter includes some examples of the use of technologies in other industries, which would help the reader to imagine the technology itself and how it could be used in an industrial context.

Moving to Chapter 3, where the applications of AI in the construction industry are defined and viewed. The structure of Chapter 3 was made to preserve the flow of the

thesis depending on the structure of Chapter 2. The benefits and challenges are discussed concerning AI technology.

In Chapter 4, five industry case studies were selected from the industry to give examples of the practical use of AI in construction. The five case studies differ in the topics, use of AI technology, and purpose. In the end, the study's conclusion is introduced, and possible future work is explained.

2 Artificial Intelligence Technologies and Tools

This chapter is designed to help the reader form a better-simplified understanding of artificial intelligence while providing an overview of different definitions of Artificial Intelligence itself. Moreover, it described and explained technologies that are mostly used in industries. To make the content more understandable, examples are given from other industries wherever relevant and found.

An important concept in computer science is artificial intelligence. With artificial intelligence, machines can be taught, logically corrected, self-programmed, and self-corrected to perform the work of humans. Logic, self-correction, and self-programming are some of the actions that artificial intelligence performs. Several scientific and applied fields rely on it extensively. Several industries, including medicine use artificial intelligence to perform surgeries accurately. Furthermore, artificial intelligence research is highly specialized. Moreover, artificial intelligence research advances learning, pattern recognition, reasoning, problem-solving, visual perception, and language comprehension. Many different factors are involved in it, such as logic, knowledge, planning, education, communication, imaging, and individual abilities. (Aggarwal et al., 2022, p. 117)

Computers, robots, or software with artificial intelligence can think intelligently in the same way as humans do. Artificial intelligence is developed by analysing the brain's cognitive processes. Artificial intelligence has helped humanity during the past six decades, and in the following paragraph, some examples of these interventions in human history are introduced. (Simplilearn Solutions, 2023)

The first artificial intelligence conference was held by John McCarthy in 1956 (Simplilearn Solutions, 2023). Fourteen years later, a mobile robot called Shakey was the first general-purpose robot built in 1969 (Simplilearn Solutions, 2023). This robot has become a more helpful tool by doing things purposefully rather than just following directions. In 1997, International Business Machines corporation (IBM) created the massive computer 'Deep Blue', which defeated the world chess champion in a match (Simplilearn Solutions, 2023). Moreover, Robotic vacuum cleaners were created in 2002. From 2005 to 2019, dancing robots, smart homes, and speech recognition have become commonplace in the past few years (Simplilearn Solutions, 2023). A

vaccine programme developed by Baidu to fight SARS-CoV-2 (COVID-19) began in 2020 with the release of its Linear Fold AI algorithm. In 27 seconds, the algorithm predicts the virus's Ribonucleic Acid (RNA) sequence 120 times faster than any other method. (Simplilearn Solutions, 2023)

Abioye et al. (2021, p. 3) Gave an overview of the Artificial intelligence types, subfields, and components shown in Figure 4. Types of AI are introduced in the following section to define Artificial Intelligence with the limitation of introducing only the weak and strong AI for their importance. At the same time, the subfields were introduced, each in a separate section following the definition of AI.

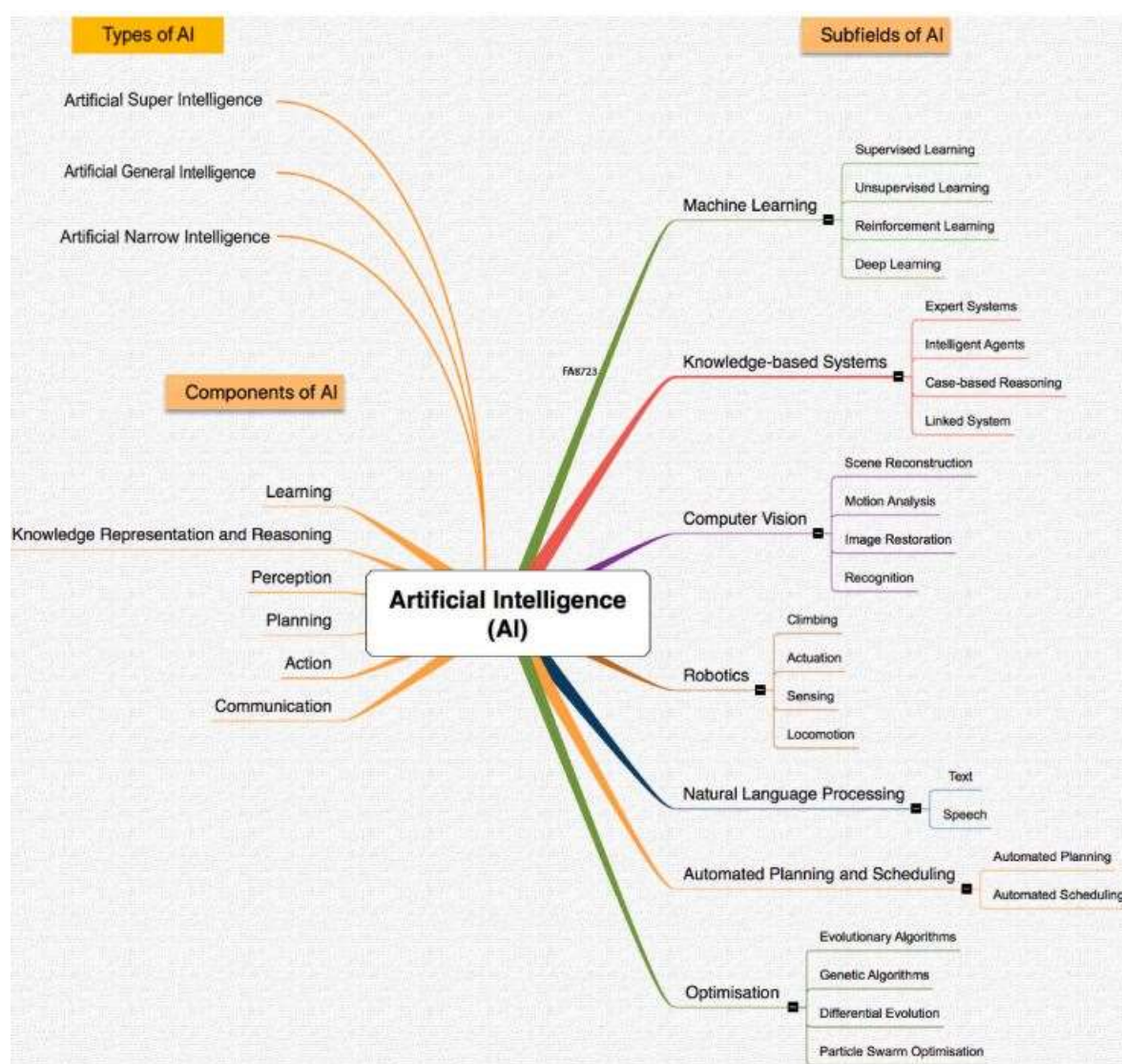


Figure 4 Subfields of AI, their components, and types (Abioye et al., 2021, p. 3)

Although artificial intelligence should have a well-known structure, it depends on the time and perspective of the researcher involved in the research. The overview given

in Figure 4 was selected since it was part of similar research interested in the role of AI in construction, and it gave a clear and straightforward description of AI overview. In the next section, the definition of AI is introduced.

2.1 Artificial Intelligence Definition

According to Aggarwal et al. (2022, p. 117), there are two types of Artificial Intelligence as science:

- **Applied:** In the weak or narrow category, artificial intelligence refers to systems that can accomplish a single task without the intervention of a human. This type refers to artificial intelligence that can perform one task, such as driving a car, without the assistance of a human.
- **Generalized:** A strong system can handle any unusual situation or obstacle and simulate the human consciousness.

Various applications and fields have been explored and developed using artificial intelligence. Medical diagnosis applications, the effect of a search engine on a computer via the Internet, and the growth of stock trading operations are also among them. Cognitive stimulation is another impressive application. This application aims to test theories of how the brain works and how it performs functions, including recognition of faces and memory activation. Through artificial intelligence, machines can “reason” and “learn” and are used to diagnose patients effectively. For example, a computer program can compare the lung X-ray image with a database to determine whether the patient has a COVID-19 infection. Artificial intelligence can complement and strengthen physicians’ diagnoses of diseases since similar applications are being developed for many other diseases. Artificial intelligence can also be used for practice planning, as it can be used to determine the best treatment based on information gathered from patients and thousands of similar cases in the past.(Aggarwal et al., 2022, p. 3)

The weak and strong AI definitions are discussed in the following section, including a comparison between both.

2.1.1 Weak and Strong AI

There are two major types of artificial intelligence, weak and strong. Because they operate within a predefined set of functions, several popular personal assistants today, including Google Assistant, Siri, and Alexa, are considered weak artificial intelligence programs. Furthermore, strong AI programs are called machines that can make decisions independently and possess their own minds without human intervention. (Khillar, 2020)

A good understanding of strong and weak AI is crucial. The following sections further discuss how strong and weak AI systems differ. For example, a strong AI system can fully operate autonomously, while a weak AI system requires human input for specific tasks.

2.1.1.1 Weak AI

Weak AI refers to AI with a limited range of functionality. It is more commonly referred to as narrow AI. Weak AI uses advanced algorithms to solve problems or make decisions but does not fully encompass the cognitive capabilities of humans. Siri and Alexa, for example, are voice-based personal assistants that operate within a predefined set of functions, which means they often respond based on programming. It simply holds that machines can model intelligent behaviour and solve complex problems with it, but it is not so enthusiastic about the outcomes of artificial intelligence. Even so, just because a machine behaves intelligently does not mean it is as intelligent as a human. (Khillar, 2020)

2.1.1.2 Strong AI

The concept of strong AI supports the idea that machines can be capable of developing human consciousness on par with humans. A strong AI refers to a program or machine capable of thinking and accomplishing complex tasks without human intervention. A strong AI-powered machine with complex algorithms can make independent decisions without human intervention. With the proper functional organization, computers can perceive, think, and intend like people. In other words, it says that a computer can perform complex tasks independently as humans can. (Khillar, 2020)

2.1.1.3 A Comparison of Weak and Strong Artificial Intelligence

The difference between both can be explained on three pillars (Meaning, Functionality and Goal). Those three pillars are summarised in Table 1:

AI type / Comparison	Strong AI	Weak AI
Meaning	<ul style="list-style-type: none"> - Machines can develop the same intelligence and consciousness as humans. - Strong AI is a theoretical form of artificial intelligence. 	<ul style="list-style-type: none"> - A weak AI (narrow AI) uses advanced algorithms to solve specific problems - solve complex reasoning problems without including human cognitive ability.
Functionality	Can be demonstrated by machines that are intelligent and self-aware.	Does not have many of the cognitive abilities that humans possess, they do accomplish a wide range of tasks.
Goal	<ul style="list-style-type: none"> - An artificial intelligence that is as intelligent as humans can be considered strong AI. - it does not necessarily incorporate knowledge of the specific problem at hand. 	To develop a technology that allows machines to solve specific problems and reason faster than humans.

Table 1 Meaning, Functionality and Goal of weak and strong AI (Khillar, 2020)

Table 1 gives an explicit clarification to differentiate between both terms. Artificial Intelligence includes many branches that work on providing smart solutions. In the following sections, each branch is discussed, including examples of use in different industries.

2.2 Machine Learning

Abioye et al. (2021) introduced Machine Learning (ML) as it involves the design and implementation of computer programs that use statistical techniques to model, control, or predict using experience and past data without explicitly programming them. It can be classified as:

- Supervised Machine Learning: focuses on how machines use information from labelled datasets, such as inputs and desired outputs, to make decisions. Simply, it predicts the next value.
- Unsupervised Machine Learning: The technology enables machines to learn essential structures from unlabelled data. Put another way, data-driven technology enables machines to discover basic structures from unlabelled data.
- Reinforcement Learning: This is called "learning from mistakes", as the system learns what is going on and what actions will result in the highest rewards.

For example, ML applications in the financial markets can automate, optimise portfolios, manage risk, and provide financial advisory services to investors (robo-advisors). (CQF Blog, 2023)

Automated trading can be achieved by constructing mathematical models analysing financial news and trading activity to determine market trends, such as volume, volatility, and possible anomalies. As soon as the system is set up and running, these models execute trades following a given set of instructions, allowing for activity without direct human involvement. In order to optimize portfolios, machine learning techniques can be used for analysing large amounts of data, identifying patterns, and determining solutions to problems balancing risk and reward. Machine Learning can also detect investment signals and forecast time series. (CQF Blog, 2023)

Using machine learning for risk management can assist in making credit decisions and detecting suspicious transactions and behaviours, including Know Your Customer (KYC) compliance and fraud prevention. A shift towards robo-advisors has been supported by machine learning for financial advisory services, assisting retail investors with their investments and savings. The relationship between Machine Learning ML, Artificial Neural Networks (ANN) and Deep Neural Networks (DNN) is

explained in Figure 5, where many construction industry applications depend on their algorithms.

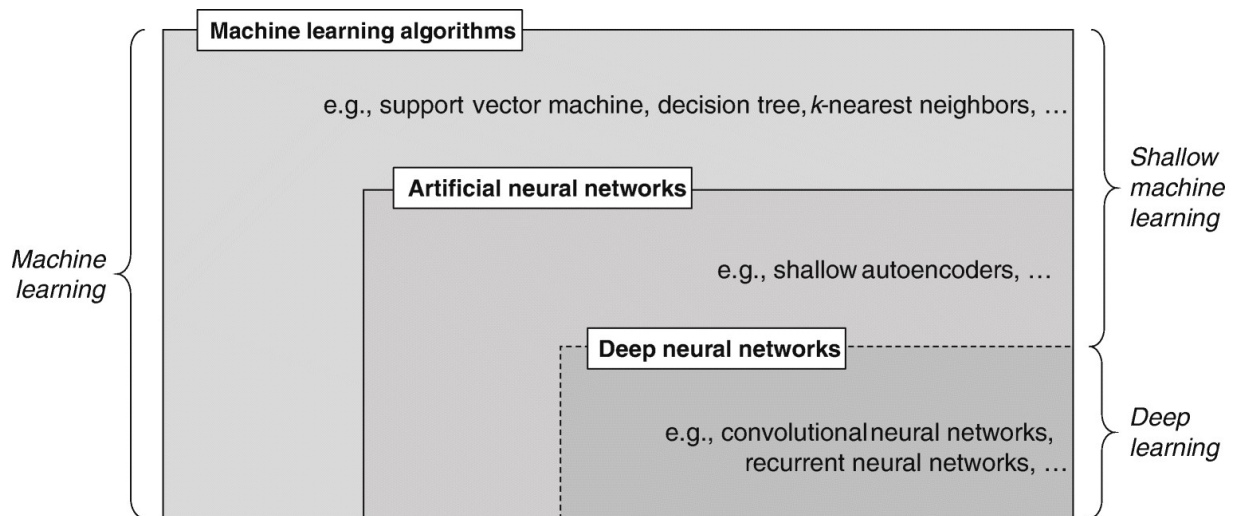


Figure 5 Classes and concepts of machine learning illustrated by a Venn diagram
(Janiesch et al., 2021, p. 687)

Figure 5 divides machine learning into shallow and deep, where the deep neural networks are also known as Deep Learning DL. The figure also cleared that DL is part of ML, where this relationship is not clear in other references.

Abourayya Abourayya (2021, p. 10) illustrated that it is common to divide the data into three parts in machine learning models: In order to train the model, we use the training dataset. In order to validate the model once it has been trained, we use the validation dataset. A final evaluation of the model is done using the testing dataset. To evaluate the accuracy of ML models, the following three factors are considered:

- There is only a small error based on the validation data.
- Test and validation sets have comparable error rates.
- It has a small error propagation rate.

In machine learning, the first two factors correspond to the issues of underfitting and overfitting, respectively. An under-fitted model has a small training error, and an overfitted model has an excessive training-test error gap. A proper fit in ML is a spot between underfitting and overfitting which can fit various functions.(Abourayya, 2021, p. 10)

The following two sections explain more about ANN and DL.

2.2.1 Artificial Neural Network

As a result of their flexibility, Artificial Neural Networks (ANN) are particularly interesting since they can be customized for a wide range of uses across all three types of machine learning because of their structure. Based on the information processing principle in biological systems, ANNs are mathematical representations of connected processing units called artificial neurons. It is similar to synapses in the brain in that weight is continuously adjusted during the learning process to increase or decrease the strength of each connection between neurons. Neurons are typically arranged in layers in networks. Signals can only be processed by subsequent neurons after an activation function exceeds a certain threshold. A typical algorithm has two layers: an input layer, which receives data input (like product images from online stores), and an output layer, which produces the final result. In between, one or more hidden layers learn a nonlinear mapping between input and output. Layers and neurons, as well as the learning rate and activation function, cannot be determined by the learning algorithm. The hyperparameters of a model can be determined using an optimization routine or manually. Artificial neural networks can approximate functions, forecast, and optimise. (Janiesch et al., 2021, p. 687)

2.2.2 Deep Neural Networks

Unlike ANN, Deep Neural Networks (DNN) usually comprise advanced neurons instead of simple neural networks. Additionally, they usually contain multiple hidden layers organized in deeply nested network architectures. They may use advanced activation functions instead of simple ones (such as convolutions) or multiple activations within one neuron. Deep neural networks can learn tasks automatically by feeding raw data and discovering the representation necessary for a given task. This is known as deep learning. (Janiesch et al., 2021, p. 688)

In contrast to shallow machine learning algorithms that are naturally interpretable by humans and, therefore, white boxes, advanced machine learning algorithms use black boxes for decision-making processes that cannot be traced without explanation. Deep neural networks outperform shallow machine learning algorithms for most applications that process texts, images, videos, speech, and audio since they are beneficial in domains with large and high dimensional data. Deep neural

networks are more difficult to interpret than shallow ML, especially when training data is limited. Shallow ML, on the other hand, can still produce superior results when there is more limited training data to work. (Janiesch et al., 2021, p. 688)

A practical example of using Machine Learning in the sports industry is given in the following section.

2.2.3 ML Example: Baseball's Statcast Data Improves Pitch-by-Pitch Decision-Making With Moneyball 2.0

Wittenberg (2022, p. 4) gave an example of how teams use data science and quantitative modelling to make pitch-by-pitch decisions that determine the game's outcome. On a tight budget, Oakland Athletics used data analysis and quantitative modelling to create a competitive line-up in 2002. Figure 6 illustrates how the cameras used for collecting the data are being distributed in a baseball stadium.

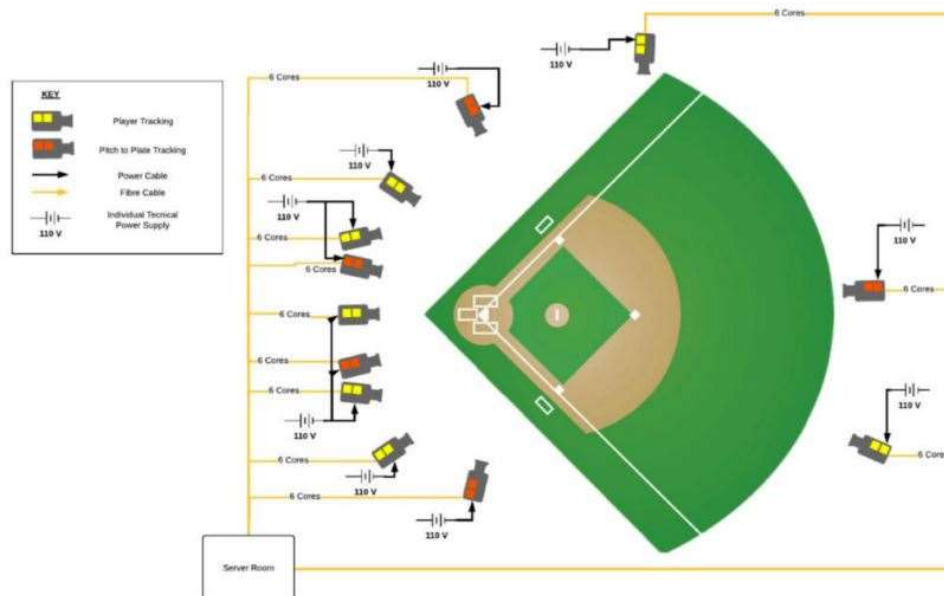


Figure 6 Cameras' location in a stadium (Wittenberg, 2022, p. 6)

2.2.3.1 Background

In the 2020 World Series, the Tampa Bay Rays made crucial decisions based on data, and the data teams needed to be faster than ever to provide analytics to coaches and players. The ability to ingest and process data faster than the competition will create a competitive advantage. Statcast provides a scalable, automated analytics platform for automating data ingestion. (Wittenberg, 2022, p. 6)

2.2.3.2 Getting the Data

Major League Baseball (MLB) provides teams access to data collected when a pitcher throws a baseball through an application programming interface (API). Statcast data is typically available every 23 seconds through the API, so data teams must request it frequently. It has been possible to collect Statcast data continuously during a game by decoupling the steps of obtaining data from the API and transforming it into valuable data by creating a code that decouples these steps. This figure simulates a restaurant waiter telling the kitchen what food a customer would like and the waiter, in this case, serving that food. The waiter here is API. (Wittenberg, 2022, p. 7)

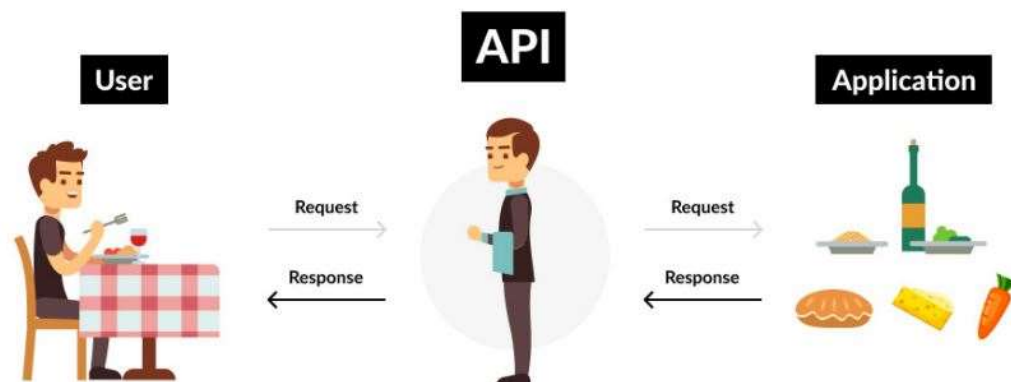


Figure 7: Using a restaurant analogy to illustrate how APIs work (Wittenberg, 2022, p. 7)

2.2.3.3 Detecting Spin Ratios and Sticky Material

Baseball adopted a new rule in 2021 to discourage pitchers from using "sticky stuff," an additive hidden in mitts, belts, or hats that, when applied to a baseball, dramatically increases spin ratios, making hitting harder. Pitchers found using sticky stuff are suspended for ten games. Oppositional coaches may request an umpire

check during a game if they suspect the pitcher has used the substance. Teams can now request from umpires that pitchers be caught using materials in real-time due to cameras capturing spin ratio data. (Wittenberg, 2022, p. 12)

In Figure 8, a combination of the theory and the result are gathered in one figure to indicate how machine learning impacted the games. To the left, the theory of spinning the ball and how it makes it harder to hit is explained. (Wittenberg, 2022, p. 12)

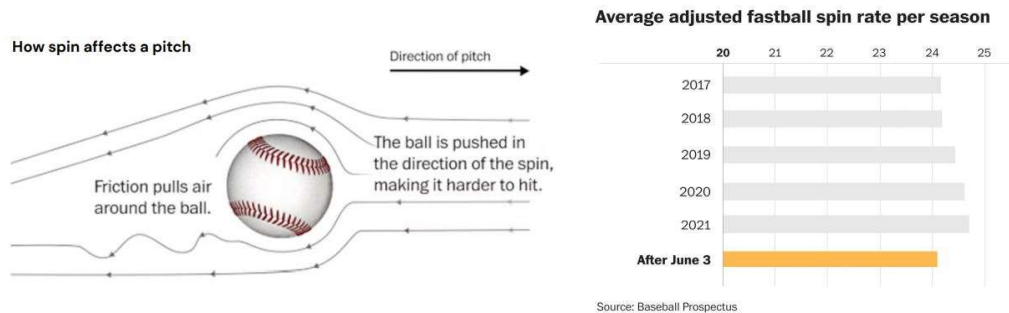


Figure 8 (To the left) Illustration of how spin affects a pitch (To the Right) Seasonal spin rate of fastballs before and after the rule was introduced (Wittenberg, 2022, p. 12)

2.2.3.4 Conclusion

Using Machine Learning models, predictions are sent to the dashboard that indicates outliers based on historical data and the pitcher's performance in the active game, allowing coaches to be alerted when a pitcher's performance falls outside the range predicted by the model. The spin ratio of the ball is tracked through the dashboard that ingests Statcast data pitch by pitch for all pitchers during all MLB games. (Wittenberg, 2022, p. 13)

2.3 Knowledge-Based Systems

A knowledge-based system is built using symbolically represented domain knowledge and predefined rules rather than complex algorithms or statistics, which are the basis of early forms of artificial intelligence (Pan & Zhang, 2021, p. 8). As a result, a computer can comprehend knowledge, facts, and beliefs based on rational reasoning and then use them to make valid conclusions and facilitate logical inferences transparently and efficiently. (Pan & Zhang, 2021, p. 8)

2.3.1 Definition of Knowledge-Based Systems

As a result of using a centralized repository of data known as a knowledge base, KBSes (knowledge-Based Systems) provide a method for problem-solving. The goal of Knowledge-Based systems is to support decision-making by capturing expert knowledge. For instance, expert systems are knowledge-based since they rely on human expertise. In addition to decision-making, KBSes can facilitate human learning and create a company-wide knowledge-sharing platform. KBSes are generally distinguished by developing knowledge through a reasoning process. The basic KBS uses an interface engine and a knowledge base. Knowledge bases are collections of information in a specific field. Similar to a search engine, an inference engine processes and locates data based on requests. Based on the data provided, reasoning systems can conclude and make decisions based on logical programming, if-then rules, or constraint-handling methods. The user interface provides users with access to the system. (TechTarget, 2023)

2.3.2 Types of Knowledge-Based Systems

TechTarget (2023) gives a brief explanation for each type of KBS as follows:

1. The expert system: simulates a human expert's decision-making in a particular area. Using expert systems to solve problems and explain their solutions is possible. (TechTarget, 2023)
2. The Blackboard system: is a multi-source information system that allows multiple sources to input new information into a system. (TechTarget, 2023)

3. The Blackboard system: relies heavily on updates from human experts to stay up to date. (TechTarget, 2023)
4. The case-based system: works by reviewing past data of similar situations to generate solutions to a problem. (TechTarget, 2023)
5. The classification system: analyzes a variety of data in order to determine its classification status. (TechTarget, 2023)
6. The eligibility analysis system: poses a series of questions that are guided by the user until the user answers a disqualifying question. (TechTarget, 2023)
7. The intelligent tutoring system: assists users with questions and provides instructions based on their performance. (TechTarget, 2023)
8. Medical diagnosis systems: are based on patient information or a series of questions where the KBS helps physicians diagnose patients and recommend treatments based on the diagnosis. (TechTarget, 2023)
9. Rule-based system: uses human-defined rules to analyse or change data to achieve a desired result. Rules might include if-then statements. (TechTarget, 2023)

By utilizing artificial intelligence technologies to process and interpret data, knowledge-based systems applications enable decision-making based on the data collected. These systems mimic humans' reasoning and problem-solving abilities using a knowledge base and rules. Healthcare is one of the prominent applications of knowledge-based systems, which assist healthcare professionals in diagnosing diseases and providing treatment recommendations. As well as identifying investment opportunities and managing risks, these systems can be used in the financial industry to analyze large amounts of data. It is also possible to apply knowledge-based systems to other industries, such as manufacturing, logistics, and customer service, where they can automate complex decision-making processes and improve operational efficiency. Knowledge-based systems applications have been shown to enhance decision-making processes across various industries.

2.4 Computer Vision and Image Recognition

From recording raw data to identifying image patterns and interpreting information, computer vision can be used to accomplish a wide range of tasks. Various techniques, ideas, and concepts from computer graphics, pattern recognition, and artificial intelligence are combined in this field. The main goal of computer vision is to gain information about events or descriptions by analyzing input scenes (digital images) and extracting features. How computer vision problems are solved depends on what the application is and what data is being analyzed. (Wiley & Lucas, 2018, p. 28)

2.4.1 Definition of Computer Vision and Image Recognition

Computer Vision (CV) combines image processing and pattern recognition. The output of Computer Vision is image understanding. Unlike Computer Graphics, Computer Vision focuses on extracting information from images. This field is developed by adapting the ability of human vision to take the information. Computer vision is a branch of computer technology whose development depends on improving the quality of images or recognizing them. (Wiley & Lucas, 2018, p. 28)

The purpose of Image Processing is to implement computations on images, such as sharpening and contrast, among others, while the purpose of Computer Vision is to develop models and extract data from images. Moreover, Human and Computer Interaction (HCI) covers all aspects of technology associated with human-computer interaction, such as design, interface, and technology. Human-computer interaction as an interdisciplinary science is a consequence of technological development, considering human factors as it mediates the relationship between humans and computers. Intending to analyze spatial data, data indexed by more than one dimension, computer vision systems are functionally similar to human vision systems. However, computer vision cannot replicate the human eye. (Wiley & Lucas, 2018, pp. 28, 29)

2.4.2 CV Example: Computer Vision Enabled by Deep Learning for Medical Applications

Many scientific fields have generated large amounts of digital data concurrently with the development of modern computer vision. Due to its remarkable ability to learn many tasks from a wide variety of data sources, DL has made many medical advances. In Figure 9, computer vision models are shown on how to recognize patterns using large datasets, ranging from physician-level diagnosis to medical scene perception. (Esteva et al., 2021, p. 2)

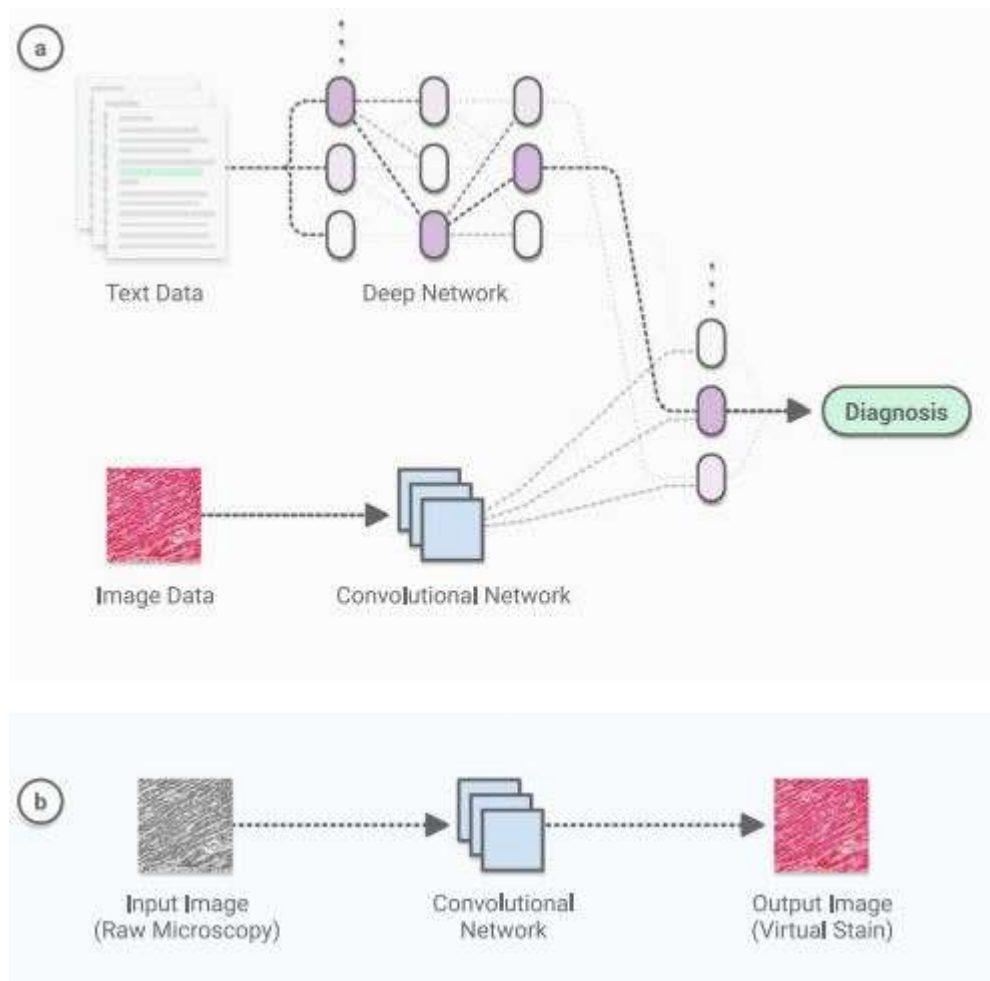


Figure 9 Example of medical computer vision tasks (Esteva et al., 2021, p. 2)

A multimodal discriminative model can be constructed by applying deep learning architectures to both image and non-image data simultaneously in the case of (a). In the case of (b), convolutional neural networks can be trained to generate images using an image-to-image regression model. Annotations learned can be used to diagnose diseases, predict clinical outcomes, and make predictions. Besides

improving super-resolution images, this model can also create original images. (Esteva et al., 2021, p. 2)

Over the past decade, a strong community of deep learning researchers has been formed through ImageNet Large-Scale Visual Recognition Challenge (ILSVRC). It has led to advances in these tasks. By 2012, the first contemporary Graphic Processing Unit-based (GPU-based) Deep Learning approach signalled the beginning of a period in which significant improvements were made throughout the competition. Many diseases have been classified and detected successfully using fine-grained versions of these medical methods, as illustrated in Figures 10 and 11.

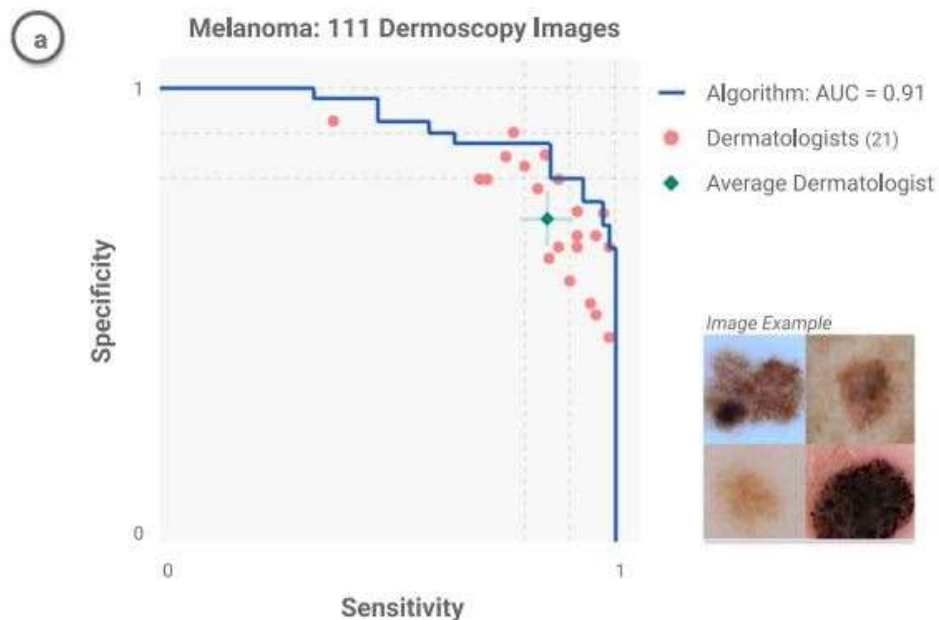


Figure 10 Physician-level diagnostic performance (a) (Esteva et al., 2021, p. 2)

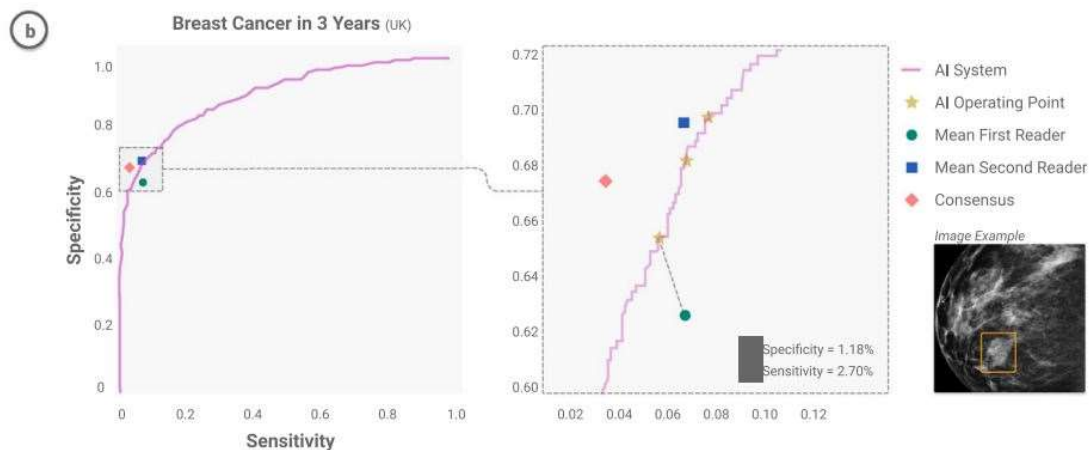


Figure 11 Physician-level diagnostic performance (b) (Esteva et al., 2021, p. 2)

2.4.2.1 Conclusion

A Convolutional Neural Network (CNN) performance is approximately on par with that of an expert in image classification. Figures 10 and 11 were examples of physician-level diagnostic performance, while (a) is an example from Dermatology and (b) is an example from Radiology. With enough data, the accuracy is often on par with or even better than an expert physicians. Microscopy segmentation of multiple types of overlapping cells has also improved substantially, particularly in complex scenarios. CNN is a critical technique in deep learning, as it hardcodes translational invariance into its algorithm, one of the key features of image data. A wide range of CV tasks has been improved using CNN, such as image registration (detecting similar points in images), image retrieval (locating similar images), and image reconstruction and enhancement. (Esteva et al., 2021, p. 3)

2.5 Natural Language Processing

Natural language processing (NLP) aims to translate a language into another, retrieve information, extract information, summarize text, answer questions, generate model-building topics, and mine opinions. In terms of language syntax, a language comprises finitely long sentences constructed with a finite alphabet set or a finite vocabulary of symbols. The number of sentences in a language can also be finite (because the alphabet and sentences are finite). The length of each sentence is limited to 1024 if the alphabet set is two and the sentences are ten sentences long. Many theoretical studies assume that language is infinite, so that some sentences could have an infinite length. (Chowdhary, 2020, p. 603)

2.5.1 NLP Definition

Natural language processing (NLP) is an artificial intelligence subfield that processes, analyzes, and interprets language-related data using computers, resulting in natural language comprehension similar to human comprehension (Pan & Zhang, 2021, p. 10). Analysis of free text data by hand leaves valuable knowledge untapped. This concern has led to using natural language processing (NLP) as a substitute for human oversight since it can process textual information more efficiently and at a lower cost. (Pan & Zhang, 2021, p. 10)

2.5.2 NLP Applications

Chowdhary (2020) argues that NLP is valuable because the World Wide Web (WWW) provides a large number of pages, at least 20 billion, that can be analyzed for valuable information. The following applications are some of the more well-known ways to use this data:

- Searching and indexing significant texts,
- Information Retrieval (IR),
- An organization of text according to categories,
- The process of information extracting (IE),
- Translation of languages automatically,
- A system for summarizing texts automatically,

- The process of answering questions (QA),
- Acquisition of knowledge,
- The generation and dialogue of text.

Alam (2022) shows the applications of NLP in business, with Figure 12 giving a graphical representation of them.

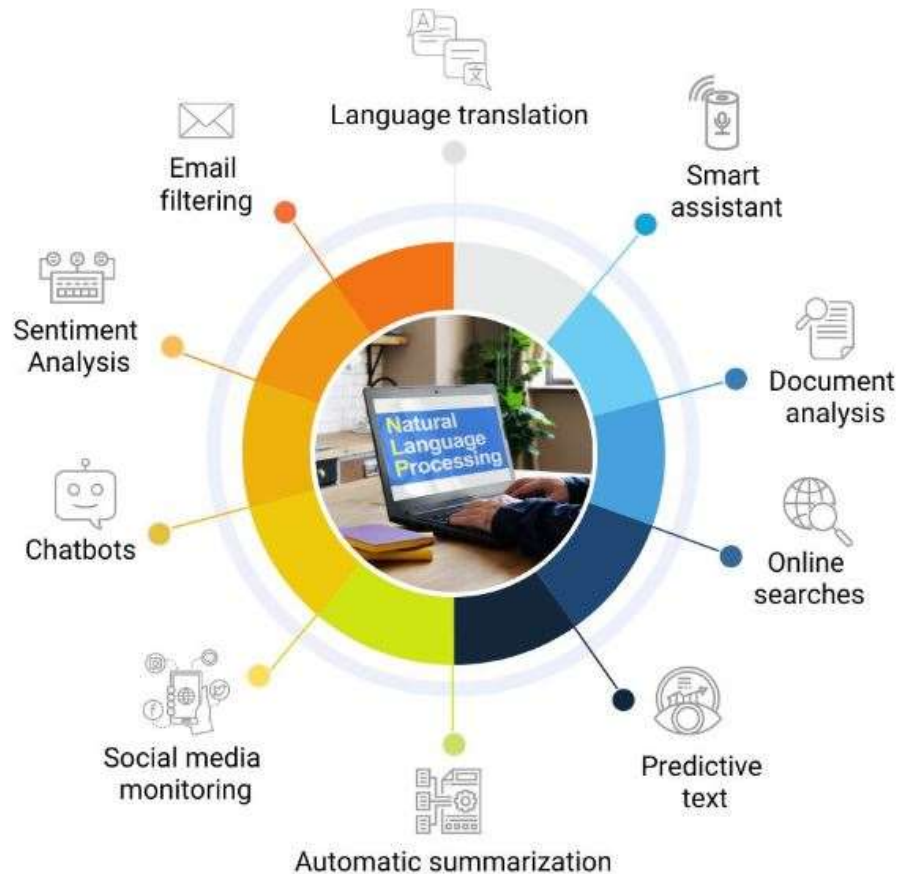


Figure 12 Applications of NLP (Alam, 2022)

Alam (2022) explained how AI successfully managed to make a computer understand human language, then answered the question of how this possibility can be used for human benefit as follows:

1. Email Filtering

Daily lives are dominated by email. Whether it is work-related, studies-related, or many other things. Emails are received in many different kinds; some are work-related, and others are promotional or spam-filled. Thus, NLP identifies and

categorizes incoming emails into "important" and "spam" and places them accordingly. (Alam, 2022)

2. Foreign language translation

Although there are as many languages as cultures, not everyone understands them all. The advent of technology has made the world a global village, and now people must communicate with people who speak unfamiliar languages. Through natural language processing, anyone can translate any language with all its sentiments. (Alam, 2022)

3. The smart assistant

A new smart device is introduced daily in today's world, making it more advanced technology that allows humankind to interact with smart assistants, such as Siri, Alexa, and Cortana. These assistants respond as one would to a human being, just in a similar manner. Natural Language Processing breaks down languages into parts of speech, root systems, and other linguistic features so the computer system can understand them. As well as helping them understand the language, it also helps them process its meaning and sentiments in the same way humans do. (Alam, 2022)

4. Analysing documents

Among the applications of NLP is document analysis. Companies, colleges, schools, and other such places always have much data that must be sorted out, maintained, and searched for. With NLP, this task can be accomplished by searching for keywords and categorizing them based on instructions. As well as assisting users in managing risk and claims, it also assists them in making informed decisions. (Alam, 2022)

5. Searching online

Search engines are the most extensive sources of information on the internet. They utilize Natural Language Processing (NLP) to understand the literal meanings of words and why they are used. (Alam, 2022)

6. Text prediction

In a similar way to online searches, predictive text is used by writers whenever they type anything. The keyboard can give suggestions if one types a few letters on the screen. Once a few words have been written, it suggests what might happen next.

These predictive texts may initially be inaccurate. However, as it learns from the written texts, it starts suggesting the next word correctly even if it has not yet written a single letter. Smartphones can learn from texting habits and suggest words based on natural language processing. (Alam, 2022)

7. Summarization automatically

It is no secret that inventions and innovations have increased the amount of data. As a result, data processing has also increased. However, there are several drawbacks to manual data processing, including its time-consuming nature and tendency for errors. The NLP solution provides a quick and flawless way to summarize information since it can summarise information and understand its emotional meanings. (Alam, 2022)

8. Analysis of sentiment

Almost all conversations and texts contain emotions, including daily conversations, content and comments, and reviews of books, restaurants, and products. As humans, it is possible to read and interpret emotions in writings and conversations, but computers can also understand them along with their literal meanings using natural language processing. (Alam, 2022)

9. The chatbot

As opposed to waiting for a short and instant response for a long time, a chatbot responds instantly and accurately. These chatbots receive conversational capabilities through NLP, so they respond to customers' needs appropriately instead of simply providing bare-bones responses. Furthermore, chatbots operate based on natural language processing (NLP), enabling them to comprehend emotions and respond accordingly when human resources are scarce or unavailable daily. (Alam, 2022)

10. Monitoring social media sites

Social media users share their opinions, likes, dislikes, and experiences, revealing a lot about them. Social media companies can use NLP to get information about their products and services to improve or amend them. In addition to finding information about individuals, it also finds information about products and services. As a result of this system, the computer system understands unstructured social media data, analyzes it, and produces value for companies. (Alam, 2022)

2.6 Robotics

Industrial robots were introduced into factories during the industrial revolution in the early 1960s to relieve humans from dangerous and hazardous tasks (Garcia et al., 2007, p. 90). Incorporating industrial robots into other manufacturing processes later increased the demand for industrial robots to be more flexible and intelligent. The current manufacturing robotics market has new needs and markets such as (cleaning, demining, construction, shipbuilding, and agriculture). (Garcia et al., 2007, p. 90)

2.6.1 Robotics Definition

In robotics, science, engineering, and technology are brought together to create machines that act similarly to humans called robots (Daley, 2023). Humanoid robots have been exaggerated as caricatures of the real thing. Robots are programmable machines that perform specific tasks, and robotics refers to the study of creating and automating them. Robots vary in autonomy from fully autonomous ones that do not require any external influence to those controlled by humans. (Daley, 2023)

In spite of the growing field of robotics, robots have some consistent characteristics. Robots utilize their mechanical constructions to perform tasks in the environment they are designed for. Programming allows robots to perform tasks when and how they should. Without programming, robots would be no more than simple machines. (Daley, 2023)

2.6.2 Types of Robots

Intel is a world-leading company in the field of technology. Based on that, this section illustrates how Intel looks at the types of robotics. It is becoming increasingly common for robotics solutions to be implemented in a growing number of industries and applications due to innovations in capabilities, price, and form factor. Thanks to advances in processing power and artificial intelligence, robots can now perform a wide range of tasks in a variety of ways in today's world. According to the applications of robots, there are six main types. (intel.com, 2023)

2.6.2.1 Autonomous Mobile Robots (AMRs)

Technology such as sensors and cameras allow Autonomous Mobile Robots (AMRs) to ingest information about their surroundings in near real-time as they travel worldwide. With the help of onboard processing equipment, they can analyse the data and make an informed decision—whether moving to avoid an oncoming worker, picking the perfect parcel, or disinfecting a surface. (intel.com, 2023)

2.6.2.2 Automated Guided Vehicles (AGVs)

These machines are commonly used to deliver materials or move items in controlled environments, such as warehouses or factories. AMRs can roam freely in the environment, whereas AGVs follow predetermined paths and often require operator supervision. (intel.com, 2023)

2.6.2.3 Articulated Robots

Articulated Robots are made to simulate the movement of a human hand. Often referred to as robotic arms or articulating robots, articulated robots perform various tasks, including welding, material handling, machine maintenance, and packaging. (intel.com, 2023)

2.6.2.4 Humanoids

Despite the fact that many mobile humanoid robots may technically fall under its domain, AMR is often used to describe robots centred around humans, often with human-like forms. As they sense, plan, and act, they use many of the same technology components as AMRs when they provide directions or concierge services. (intel.com, 2023)

2.6.2.5 Cobots

In contrast to other types of robots that work alone or in strictly isolated environments, Cobots can be used in conjunction with humans. Cobots can sometimes be used to help humans accomplish more by responding to their movements and learning from them. They can also eliminate manual, dangerous, or strenuous tasks from day-to-day workflows. (intel.com, 2023)

2.6.2.6 Hybrids

As a result of the combination of different types of robots, hybrid robots can perform more complex tasks, such as handling packages in a warehouse. An AMR and robotic arm could be combined to create such a robot. Whenever capabilities are

consolidated into single solutions, compute capabilities are also consolidated. (intel.com, 2023)

2.6.2.7 Unmanned Aerial Vehicles (UAVs)

UAVs are controlled aerial vehicles that can perform a variety of missions without human assistance. It is possible to control these robots remotely using various electronic gadgets such as microprocessors and sensors. When human intervention is dangerous in an area, UAVs can perform operations autonomously. (Mohsan et al., 2023, p. 111)

2.6.3 Examples of Robotics Applications

Robotics have enormous applications in all industries nowadays. Some examples of those applications are as follows:

2.6.3.1 Manufacturing with Robotics

In the manufacturing industry, robots have been used for decades. Cars and industrial equipment can be tested and assembled efficiently with the help of robots and co-bots (robots that work with humans). Approximately three million industrial robots are currently in use, according to estimates. (Daley, 2023)

2.6.3.2 Using Robots in Logistics

The use of robots for shipping, handling, and quality control has become an indispensable part of logistics companies and retailers. Logistics companies are using robots in warehouses, as well as on the road, to increase efficiency in order to make sure the packages arrive as quickly as possible. Items are being taken off shelves, transported across the warehouse floor, and packaged by robots. Also, last-mile robots (robots that deliver packages autonomously) have gained popularity. (Daley, 2023)

2.6.3.3 Automated Home Appliances

Robots are available in the market to help at home. Robots can now mow lawns, clean pools, and sweep floors all by themselves. The most popular robots in the home are the Roomba vacuum cleaner and the vacuum Bot. (Daley, 2023)

2.6.3.4 Using Robots to Travel

It is now becoming more and more commonplace for self-driving vehicles to be developed using a combination of data science and robotics. Self-driving cars are no longer science fiction; automakers are taking over the world. Rideshare companies such as Uber and Lyft have developed autonomous vehicles that do not require human operators. (Daley, 2023)

2.6.3.5 Robotics in the Healthcare Industry

The healthcare industry has seen tremendous advances in the field of robotics. Healthcare professionals use these wonders to perform surgeries and assist patients in recovering from physical therapy injuries in almost every aspect of the field. Robots in healthcare include Toyota's healthcare assistants, which help people walk again, and Timed Up and Go tests (TUG), which autonomously deliver medicine and clean linens. As well as filling and sealing testing swabs, some manufacturers use robotics to produce respirators and personal protective equipment PPE to fight COVID-19. (Daley, 2023)

2.6.4 Uses of Different Types of Robotics in Industries

As introduced in the previous section, robotics can be used in many applications. It is just a matter of research and ideas to think about which robot to perform which task. Table 3 indicates how an industry would use a robot type. The table indicates the field and the application per the given industries.

Industry	Robot Type	Field	Applications
Industrial	<ul style="list-style-type: none"> - AMRs - AGVs - Articulated Robots - Cobots 	<ul style="list-style-type: none"> - factory floors - warehouses 	<ul style="list-style-type: none"> ✓ help expedite processes ✓ drive efficiency ✓ promote safety
Farming and Agriculture	<ul style="list-style-type: none"> - AMRs 	<ul style="list-style-type: none"> - Harvest crops 	<ul style="list-style-type: none"> ✓ assess ripeness. ✓ move any branches or leaves ✓ Pick the crop precisely and delicately
Healthcare	<ul style="list-style-type: none"> - AMRs - Cobots 	<ul style="list-style-type: none"> - enhance the patient experience - assist medical professionals 	<ul style="list-style-type: none"> ✓ deliver medication, ✓ disinfect surfaces, ✓ provide mobile telepresence ✓ help nurses better serve their patients.
Logistics	<ul style="list-style-type: none"> - AMRs - AGVs 	<ul style="list-style-type: none"> - warehouse robots 	<ul style="list-style-type: none"> ✓ process items ✓ expedite operations ✓ increase accuracy ✓ The last mile shipment ✓ safe delivery
Smart Cities	<ul style="list-style-type: none"> - Humanoid robots - AMRs 	<ul style="list-style-type: none"> - create smarter and safer cities 	<ul style="list-style-type: none"> ✓ deliver goods ✓ conduct routine security patrols ✓ expedite building construction ✓ conduct site surveys ✓ collect building modelling information

Table 2 Robot types and their applications in different industries (intel.com, 2023)

As seen in Table 3 above, the AMRs are the most used robots in most industries. Five different industries were briefly explained: the industrials, farming and agriculture, healthcare, logistics and smart cities.

2.7 Internet of Things (IoT)

Researchers have focused heavily on the Internet of Things (IoT) in recent years. IoT is regarded as a future Internet component comprising billions of intelligent devices. The Internet of the future will be a heterogeneous network of devices with physical entities and virtual components that will expand the world's boundaries. As connected objects gain new capabilities, they can connect to the Internet of Things. (Li et al., 2015, p. 243)

Among other things, British technology pioneer Kevin Ashton (IoT) described a system in 1999 that connects physical objects to the Internet through sensors (Rose et al., 2015). As an illustration of how Radio Frequency Identification (RFID) tags can be connected to the Internet in corporate supply chains, Ashton coined the term to illustrate how goods can be counted and tracked without human intervention (Rose et al., 2015). As a result of the Internet of Things, several items, devices, sensors, and everyday objects are linked to the Internet and can process data. Many items, devices, sensors, and everyday objects connected to the Internet can process data as part of the Internet of Things. (Rose et al., 2015)

2.7.1 Definition of IoT

Despite its global buzz, the Internet of Things cannot be defined in a single, universally accepted way. Although some definitions refer to the Internet and the Internet Protocol (IP), others do not. Different groups use definitions to describe or promote their views on IoT and its essential attributes. IoT (Internet of Things) is defined as a trend involving the communication of embedded devices over the Internet as described by the Internet Architecture Board (IAB) (Rose et al., 2015). In many cases, these "smart objects" do not belong to humans; they are found as components of buildings, cars, or other parts of the environment but are controlled by sensors. (Rose et al., 2015, P. 11)

2.7.2 Models of IoT

IoT devices connect and communicate with each other in three different ways. This discussion presents a technical communication model framework and explains its key features. (Rose et al., 2015)

2.7.2.1 Device-to-Device Communications

Two or more devices can communicate without needing an application server intermediary using a Device-to-Device communication method. These devices can be communicated with several types of networks, including IP networks or the Internet. As illustrated in Figure 13, these devices often communicate via Bluetooth, Z-Wave, or ZigBee protocols. (Rose et al., 2015)



Figure 13 Communication model for Device-to-Device (Rose et al., 2015, P. 13)

Through these Device-to-Device networks, devices adhering to a certain protocol can communicate and exchange messages to perform their function. Due to the small data packets of information that they typically use for communicating between devices with low data rates, applications such as home automation systems typically use this communication model. (Rose et al., 2015, P.13)

2.7.2.2 Device-to-Cloud Communications

For the exchange of data and control of message traffic, devices connected directly to cloud-based services like application service providers exchange data and control messaging traffic through device-to-cloud communication. An example of this approach is bringing a device into a cloud service using existing communication mechanisms, such as Ethernet or Wireless Fidelity (Wi-Fi), to connect with the IP network. Figure 14 shows how this is done. (Rose et al., 2015, p. 14)



Figure 14 Communication Model Diagram for Devices-to-Clouds (Rose et al., 2015, P. 14)

As illustrated in Figure 14, this communication model is used by many consumer IoT devices, such as Nest Labs Learning Thermostats and Samsung Smart TVs. With the Nest Learning Thermostat, data is transmitted to a cloud database, which can then be analyzed for energy savings. Users can also update their thermostats remotely using smartphones or Web interfaces through this cloud connection. (Rose et al., 2015)

2.7.2.3 Device-to-Gateway Model

Using the device-to-gateway model, an IoT device can be connected to a cloud service via an ALG (Application Layer Gateway) service. In other words, a local gateway device consists of application software that acts as an intermediary between the device and the cloud service, translating data or protocols, providing security, and other functions. Figure 15 shows the model. (Rose et al., 2015, P. 15)

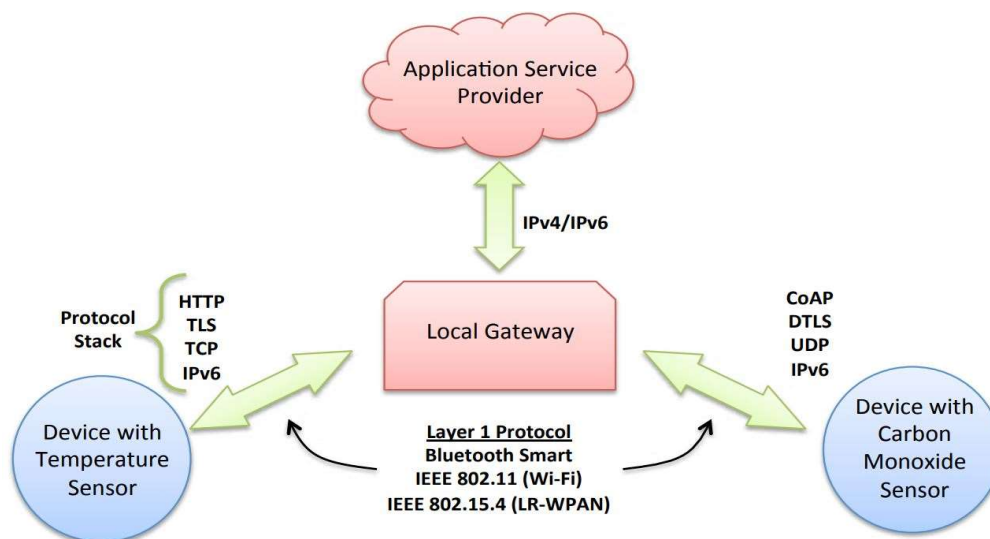


Figure 15 Communication model between devices and gateways (Rose et al., 2015, P. 15)

Several forms and applications for the Device-to-Gateway Model are indicated in Figure 15. Many consumers use this model to connect to a remote device with an app running on their smartphone. This is the most common form of this model. (Rose et al., 2015, P. 15)

2.7.3 IoT Industrial Use Cases

Despite the rapid growth of the Internet of Things, its uses have gone beyond just monitoring equipment behaviour. IoT data must be collected, analysed, and combined with sophisticated analytics to gain insight and take quick action. New industrial IoT applications emerge when IoT is combined with sophisticated analytics to rapidly process large amounts of data. (RTInsights & Siemens, 2021)

2.7.3.1 Use case 1: Remote Condition Monitoring and Remote Service

COVID-19 restrictions severely limited onsite activities due to travel bans and closed facilities. If businesses learned anything from the pandemic, they should work remotely (RTInsights & Siemens, 2021). It was, therefore, impossible to routinely check the status of machines or service them. When the pandemic hit, industrial IoT devices provided multiple advantages to businesses. Connected IoT devices can help businesses remain productive and efficient, even after things return to normal. IoT devices enable access to equipment performance data using connected IoT devices wherever needed. (RTInsights & Siemens, 2021)

Following are some examples for Use Case 1:

2.7.3.1.1 Monitoring Equipment in Real-time to Spot Potential Problems

It is possible to predict impending failure when an equipment failure occurs outside its average temperature or pressure range. Other metrics, such as customized key performance indicators, can also be used. With this real-time status data, organizations perform proactive maintenance instead of traditional calendar-based maintenance, where equipment is inspected and serviced on a set date. (RTInsights & Siemens, 2021)

2.7.3.1.2 Performing Maintenance Remotely

Service organisations can remotely perform software maintenance by connecting to equipment remotely without physically visiting. Software, firmware, and service contract updates can be pushed through a conduit with the proper connectivity and

security features. It is also common to be able to restart equipment remotely, which is frequently enough to restart a unit that is not working correctly. Performing these processes remotely reduces travel costs compared to onsite maintenance. (RTInsights & Siemens, 2021)

2.7.3.1.3 Leveraging Predictive Capabilities

AI or machine learning-based analytics are used to analyse real-time and historical data from IoT devices can provide enhanced benefits. These sophisticated analyses can predict failures by spotting trends that could lead to them. By interpreting the asset's failure, Original Equipment Manufacturers (OEMs) and service organizations can identify parts or equipment that are likely to fail before their scheduled replacement and maintenance times. Having this capability allows spare parts not to be overstocked. (RTInsights & Siemens, 2021)

2.7.3.1.4 New Business Models

Businesses can develop new business models using IoT devices and analytics. Rather than selling equipment, they can offer premium service contracts that involve remote management and monitoring. By ensuring that proactive maintenance can extend the life of an installed unit and spot problems before they occur, an organization can provide more stringent performance and uptime guarantees. A service level agreement (SLA) can quantify these promises at a premium price. (RTInsights & Siemens, 2021)

2.7.3.2 Use Case 2: Shop Floor Connectivity and Performance Monitoring

Data can be analysed and used to ensure that machines remain healthy and productive and provide complete transparency into their operations. It is possible to use IoT data to plan maintenance and spot problems in advance. IoT can also be used strategically in order to optimize operations. With IoT, machine performance can be tracked in real-time, which has never been possible. Alarms can be triggered when a system behaves differently from its normal state. Service activities can also be planned more efficiently with IoT data. If a machine is overheated or under pressure, it can be corrected. (RTInsights & Siemens, 2021)

2.7.3.2.1 The Connected Shop Floor

Data analysis can optimise machine performance, whether a single machine or an entire production line. Key performance indicators (KPIs) can be developed using this

data to optimize important figures, such as production, quality, and efficiency. Machines and plants can be compared according to this information by organizations. An Overall Equipment Effectiveness (OEE) measurement can be derived from the performance data, the quality rate, the speed of the machines, and the availability (up or down, for example). (RTInsights & Siemens, 2021)

It is possible to analyze the IoT data and the performance indicators to identify patterns and understand the interdependencies that affect (OEE) and production by analyzing data. Identifying an underperforming machine could allow it to be adjusted to meet specifications. IoT performance monitoring data can also indicate that a critical part needs to be replaced or is degrading and must be replaced. It can be highly beneficial to integrate it with other processes and workflows. (RTInsights & Siemens, 2021)

2.7.3.3 Use case 3: Closed-loop digital twin

Insights into a physical asset's operation can be gained from digital twins, which combine simulations, machine learning, and artificial intelligence with ingested data from IoT sensors. IoT devices' live performance data is pushed into the product and production digital twins in near real-time in a closed-loop digital twin. To improve product design, monitoring, and management, original equipment manufacturers OEMs increasingly use closed-loop digital twins to improve simulations. Organizations servicing or operating equipment can also use a digital twin to determine performance and troubleshoot problems. Digital twins can serve various purposes, including monitoring and improving operations, evaluating what-if scenarios, and improving the design of devices. (RTInsights & Siemens, 2021)

2.7.3.3.1 Operational Twin

The use of equipment incorrectly can cause problems. For instance, a device operating at temperatures or pressures outside its recommended range may operate faster than intended. Digital twins of parts can detect such out-of-specified conditions, adversely affecting the device and leading to an unexpected breakdown or aggressive degeneration. If not, modifications can be made to optimize a device's performance in a working environment. Simulations can assist in determining whether to push or run a device's performance. (RTInsights & Siemens, 2021)

2.7.3.3.2 Predictive Twin

With a closed-loop digital twin, what-if scenarios can be analyzed. The same simulation can be used to evaluate the impact of a speed increase on the equipment. If a device's speed increases, the output will be improved immediately. Depending on the outcome, it may require more frequent maintenance or fail sooner. The increased cost of maintaining or replacing the equipment could be compared with running the device at a higher rate. (RTInsights & Siemens, 2021)

2.7.3.3.3 Loopback to Product Design and Marketing

A product design team may gather data on field equipment as part of the product development process. In specific environments, devices may perform better than their stated specifications. This is to improve, tweak, or add enhanced features relevant to the field. Likewise, if the device performs better than its stated specifications, sales and marketing may be able to share that information with other customers within the same environment. (RTInsights & Siemens, 2021)

2.7.3.4 Use case 4: Energy Management (for production)

In 2019, industrial applications consumed over a third of The United States of America's (U.S.A) energy. As organizations look for better ways to manage their energy use and reduce costs, they are increasingly relying on industrial IoT. A key component of successful energy management is accessing and analyzing energy information to extract key indicators. Industrial organizations cannot monitor the shop floor's energy consumption in real-time. Industrial IoT can monitor granular consumption data to identify energy efficiency gaps and detect abnormal energy consumption patterns. Granular data can identify energy efficiency gaps and detect abnormal consumption patterns. (RTInsights & Siemens, 2021)

Data such as power consumption, pressure, temperature, and speed can be recorded by IoT devices on a shop floor for energy efficiency monitoring. In order to determine how much energy is being used at a particular time, plant managers examine the data to identify patterns. A simple calculation can indicate if an older model uses more energy than a new model if it is not energy efficient. In places with variable pricing, machines can be run at lower costs at certain times of the day or variable pricing rates using IoT monitoring. Heavy energy consumption can be time-shifted using IoT. In addition to reducing energy costs, IoT and energy management can also identify machines that consume a lot of energy. Facility data can be

collected and analyzed to identify machines that consume a lot. Data and insights can also be used to forecast biweekly energy needs by energy providers, in addition to the government deducting manufacturers' tax liabilities if they reduce energy consumption. (RTInsights & Siemens, 2021)

3. Applications and Challenges of Using Artificial Intelligence in Construction

Artificial Intelligence is changing the nature of industries, as illustrated in Chapter 2. AI is adopting different technologies where; each has a particular characteristic and could be used to perform tasks. Using those technologies mostly depends on how to use them and how they could differ from traditional methods and approaches. Combining two or more AI technologies can solve complex problems or provide an intelligent solution that saves time and money.

The construction industry is known to be slow in adopting new technologies. However, AI was introduced in construction in 1974 and was exponentially developed in the 21st century. The applications of AI in construction are wide and exist, but most who work in the industry still think it is part of science fiction. AI is used in the AEC industry to prevent cost overruns, provide better designs, risk mitigation, project planning, enhance job site safety and remote monitoring.

The following section illustrates applications for each branch of AI, while each can perform different tasks and provide various solutions. While at the end of this chapter, the challenges of implementing AI into construction are explained.

3.1 Machine Learning in Construction Industry

By using machine learning, machines can learn without being explicitly programmed. Machines can self-learn and forecast outcomes by using statistically significant patterns in the data they receive. Rather than being programmed by humans, they use software that has algorithms that allow them to make predictions. Machines, for example, can alert when preventative maintenance is needed based on data they collect from the equipment they monitor. Rather than sounding science fiction, machine learning is considered a subset of artificial intelligence (AI). (George J. Newton, 2022) Applications of Machine Learning in construction are discussed in the following section.

3.1.1 Machine Learning Applications in Construction

Machine learning applications in construction are still limited; day by day, they are evolving into different aspects of the field. Both (Ellis, 2022; George J. Newton, 2022) introduced the key three features of ML in Construction as follows:

3.1.1.1 Aim for Better Design Quality

A workspace startup, WeWork (workspace startup), designed its meeting room to match how people would use it to make the space more beneficial for their ultimate human users. In order to understand how often meeting rooms will be used, the workspace startup used machine learning. Before construction, the company customized the meeting rooms to fit the needs of people. Workers can detect mistakes and omissions in a design before it is built using a Machine Learning model. In addition to providing many other benefits to designers, ML can help them with many other tasks in the future. It is even possible to test various environmental conditions and scenarios using ML. Using ML, designers can determine whether an element of their design is optimal or whether it will cause problems in the future by evaluating it. (Ellis, 2022; George J. Newton, 2022)

3.1.1.2 Enhance Job Site Safety

The use of ML in photos submitted to Engineering News Record's annual Year in Construction Photo Contest is an example of how high-tech ML can improve construction site safety. Using this approach, Engineering News-Record illustrates the power of ML. In 2016, Very Intelligent Neural Network for Insight and Evaluation (VINNIE) artificial intelligence was compared with human safety experts to check for safety within images. By performing this test, a tool like VINNIE could sort through data quickly and provide relevant results for specialists. The results could then be examined in greater detail by specialists. Machine learning has the potential to learn to spot safety issues more efficiently, even though human experts are better at detecting them. (Ellis, 2022; George J. Newton, 2022)

3.1.1.3 Risk Assessment and Risk Reduction:

Recognizing risks before they occur is one of the most interesting aspects of machine learning. Using predictive analytics, ML can identify risks, analyse their impact, and reduce them. This allows humans to identify risks and prevent them from arising. (Ellis, 2022; George J. Newton, 2022)

3.1.2 Artificial Neural Networks Applications in Construction

As a mathematical model and a software or hardware implementation, artificial neural networks (ANNs) have been developed to mimic what happens in living organisms - nervous networks in the brain. Construction applications of artificial neural networks (ANNs) are discussed below.

3.1.2.1 Estimated Cost of Construction

Construction projects can be predicted using neural networks, and construction costs, materials, and production rates can be estimated using neural networks. (Doroshenko, 2020, p. 2)

3.1.2.2 Efficiencies and Consumption of Energy

Using ANN, heating and cooling system load can be forecasted, energy consumption can be analysed, and electricity consumption can be calculated. Besides its use for heat insulation, neural networks can also be used to study the heat insulation properties of building walls and materials and also to heat, ventilate, and air condition a building. (Doroshenko, 2020)

3.1.2.3 Materials Used for Construction

Building material properties can be predicted using neural networks, for example, by comparing the compressive strength of mortars containing micro-silica and calcium inosilicate minerals. (Doroshenko, 2020, p. 2)

3.1.2.4 Mechanics of Soils

In order to identify changes in soil properties, ANNs are used to detect seismic signals caused by soil vibrations and earthquakes. Thus, seismic activity and potential seismic hazards can be predicted. ANNs are also used to analyze seismic data and to interpret earthquake characteristics. (Doroshenko, 2020, p. 2)

3.1.2.5 Smart Cities

Artificial Neuronal networks serve various functions in smart homes, including security, temperature control, water supply, ventilation, lighting, reminders, and monitoring and evaluation systems for objects. (Doroshenko, 2020, p. 2)

3.1.2.6 Analysing Structures

Many tasks in structural analysis use neural networks, such as assessing concrete strength and structural performance. (Doroshenko, 2020, p. 2)

In conclusion, the provided examples for ML and ANN are not inclusive but represent most use cases in the industry. Furthermore, both previously mentioned technologies can be used with other technologies, such as Computer Vision, to provide innovative solutions. In the following chapter, a case study discusses the use of DL and CV for safety analysis and detection.

3.2 Computer Vision and Image Recognition in Construction Industry

The construction industry is increasingly relying on computer vision. Construction professionals can use computer vision technology to identify potential safety hazards and monitor construction progress using cameras and machine learning algorithms.

3.2.1 Computer Vision and Image Recognition Applications in Construction

Computer vision technology is making a massive impact on the construction industry. AI vision is revolutionizing the construction industry, driving greater efficiency and productivity. It enables the industry to identify potential safety hazards quickly. It also provides real-time analytics and progress reports. (Safari, 2023) Applications of computer vision in the construction industry can be illustrated as follows.

3.2.1.1 Construction Equipment Detection and Tracking

Using machine learning, Computer Vision can identify cranes, bulldozers, excavators, and loaders based on their movement and presence. By doing so, they can ensure machines are used efficiently and reduce waiting times in specific locations. Intelligent solutions use object detection algorithms to detect construction vehicles and prevent machinery from blocking walkways and exits. (Boesch, 2023)

3.2.1.2 Managing and Maintaining Assets with Computer Vision

Construction asset condition monitoring can help managers determine which assets need to be repaired or replaced, making asset management more effortless. This tool can assist workers with maintenance by alerting them when assets need to be repaired or replaced. AI vision intelligence can extend the life of assets, reduce waste, and cut costs and delays associated with interruptions and delays. (Boesch, 2023)

3.2.1.3 Controlling Quality with Automation

Using computer vision to control construction materials' quality automatically is possible. By detecting irregularities in the materials early in the production process, errors can be reduced, and the overall quality of the finished product can be improved. By detecting defects early on in the production process, errors can be reduced, and the overall quality of the finished product can be improved. Construction companies can take corrective action to prevent further damage from

occurring if any defects are identified. For example, AI vision could be used to inspect the quality of concrete used in a building project. (Boesch, 2023)

3.2.1.4 Analysing and Optimizing Processes

By tracking the progress of construction projects with computer vision technology, project managers can identify potential problems early and understand how the project is developing. It is, therefore, possible for project managers to optimize the construction process and ensure that projects are completed on schedule and within budget. (Boesch, 2023)

3.2.1.5 Tracking and optimizing processes

By tracking the progress of construction projects with computer vision technology, project managers can identify potential problems early and understand how the project is developing. Therefore, project managers can optimize the construction process and ensure that projects are completed on schedule and within budget. (Boesch, 2023)

3.2.1.6 Using a Distance Meter or Volume Meter

Machine learning applications can measure distances, angles, and other dimensions. For budgeting and planning purposes, a computer vision tool can also measure the volume of construction materials. As a result, construction companies can accurately calculate the materials required, which is beneficial for budgeting and planning. For instance, it can help create blueprints and map construction sites. Truck counts on a construction site can also determine material volume. (Boesch, 2023)

3.2.1.7 Infrastructural Scanning Using 3D Technology

As-built models of existing structures can also be created with computer vision. Buildings are renovated or expanded using point clouds, taken from many angles, and combined into one 3-D image. Architects and engineers use point clouds to understand objects in 3D. Point clouds can be used for modelling objects or analysing distances. (Boesch, 2023)

3.2.1.8 Mapping both outdoors and indoors

Indoor and outdoor mapping can be developed using computer vision techniques, with outdoor mapping primarily as a navigation tool, while indoor mapping may serve as a tracking tool for people or objects within a room. (Safari, 2023)

3.2.1.9 Enhance the Safety of the Workplace

Safety monitoring can be automated with computer vision in construction, and dangerous situations can be detected automatically. Wearing Personal Protective Equipment (PPE), such as hard hats, safety glasses, gloves, and vests, can be detected using computer vision software. When software detects that someone is not wearing a vest, it can automatically alert a supervisor so they can take action, reducing the risk of struck-by injuries. To reduce the risk of caught-in/between injuries, CV can also recognize when workers enter unsafe areas or stand under loads. In addition to detecting exceeded speed limits, CV can also monitor for ergonomic injuries caused by repetitive movements. It can also monitor for fall protection in areas not meeting fall protection standards. (Safari, 2023)

In conclusion, computer vision application to construction has revolutionized the industry by enhancing safety, improving quality control, automating progress monitoring, and providing advanced 3D visualization capabilities. With the advancement of technology, computer vision will continue to impact the construction sector as it continues to evolve significantly.

3.3 Natural Language Processing in Construction Industry

By analysing and extracting meaningful insights from vast amounts of textual data generated during construction projects, Natural Language Processing (NLP) is a valuable tool in the construction industry. By identifying patterns, extracting key information, and facilitating decision-making, NLP techniques can be used to process construction documents.

3.3.1 Natural Language Processing Applications in Construction

Text data analysis using NLP can help construction professionals save time and money, improve accuracy, and improve project management. Applications of NLP in construction are discussed in the following section.

3.3.1.1 Use in Contracts

To prevent ignoring requirements, NLP can classify clauses as requirements or non-requirements or as distinct categories (e.g., construction, design, operation, and maintenance). Additionally, NLP can detect biased/poisonous clauses and significant contract changes. Alternatively, it can assess risks, select bidders, and predict litigation results to help resolve disputes. (Wu et al., 2022, p. 16)

3.3.1.2 Use of NLP in Safety

Using Natural Language Processing (NLP), predicting and classifying safety risks based on risk levels or types (such as environmental, financial, and political) is possible. (Wu et al., 2022, p. 16)

3.3.1.3 Schedule and Cost Management

By analyzing natural language processing, schedules can be monitored, deviations detected, and cost overruns (severe, normal, and underruns), and the cost index can be calculated. (Wu et al., 2022, p. 16)

3.3.1.4 Infrastructure Operation and Maintenance Management

Evaluate incident severity, prioritise O&M actions, and provide advice for future infrastructure projects. (Wu et al., 2022, p. 16)

3.4 Robotics in the Construction Industry

As in other industries, robotics applications in construction are meant to automate processes and safely perform dangerous tasks. Different types of robotics are being used for different construction works. The following section will discuss the applications of robotics in construction.

3.4.1 Robotics Applications in Construction

Robotics, as illustrated in Chapter 2, can be divided into different types, and each has different roles and tasks that could be done. Within the following sections, applications of robotics in the construction industry are illustrated.

3.4.1.1 Using Robotics in Construction to Build Walls

In the bricklaying process, robotics control the loading, cutting, routing, and placing of bricks, and computerized design is used to complete the process. Steel, aluminium, and carbon fibre composites construct the entire system. (ConstructionPlacements, 2023)

3.4.1.2 Unmanned Autonomous Equipment

In the world of autonomous vehicles, built robotics executives boast that their autonomous system for construction equipment, such as excavators and bulldozers, is far superior to many others. (ConstructionPlacements, 2023)

3.4.1.3 Robots with Smart Imaging Technology

The construction industry can benefit significantly from robotic automation, which improves worker safety, productivity, efficiency, and production flexibility. (ConstructionPlacements, 2023)

3.4.1.4 Using Construction Robotics for Remote Operation

An excavator or bulldozer operated remotely allows the person operating it to work where it is safest. A remote-control excavator or bulldozer allows a person operating it to work from a steady location, ensuring the operator's safety and the safety of everyone on the job site. (ConstructionPlacements, 2023)

3.4.1.5 Performing Site Inspections, Surveillance, and Surveys

Many assessments require evaluating the workplace and surrounding environment before, during, and after construction projects. Construction robotics and drones can

assist with all these procedures, monitoring personnel and securing the location. (ConstructionPlacements, 2023)

3.4.1.6 Using Unmanned Aerial Vehicles and Drones to Create 3D Maps

UAVs allow for continuous data updating and storage online, which can be viewed interactively. It offers 3D object creation and area orthophotography maps. Detects illegal construction and provides financial and investment information to investors and clients. (Anwar et al., 2018)

3.4.1.7 Using Unmanned Aerial Vehicles and Drones for 3D Scanning and Aerial Photography

During the early stages of construction, users can view 3D views of future windows during landscaping and interior design planning. (Anwar et al., 2018)

3.4.1.8 Using Unmanned Aerial Vehicles and Drones for Tracking Construction Progress

An agreed-upon flight path can be made around a development site as a visual progress report during construction (or even before). Achieving key milestones is captured by conducting ad hoc visits monthly or twice monthly to monitor the development process. The ad hoc visits serve as a record of progress for developers, stakeholders, and even the people on site. (Anwar et al., 2018)

3.4.1.9 Using Unmanned Aerial Vehicles and Drones for Volume Measurement

Measuring large areas (2D and 3D) can be done quickly and efficiently without disrupting normal operations on the site. (Anwar et al., 2018)

In conclusion, construction has been revolutionized in several ways by the use of robotics. These advanced machines have proven efficient and effective at completing once time-consuming and labour-intensive tasks. Robotics enhances safety on construction sites and improves productivity by automating repetitive and dangerous tasks. As robots reduce costs and minimize errors, construction projects will be higher quality. Technological advancements will undoubtedly lead to increased integration of robotics in construction, shaping the industry's future in general.

3.5 Internet of Things in the Construction Industry

As a result of IoT, construction managers and workers can monitor equipment performance remotely, track material inventory, and detect safety hazards remotely. As a result of this technology, construction processes can be streamlined, costs reduced, and project outcomes can be improved. In the following section, the application of IoT is explained.

3.5.1 Applications of IoT in Construction

IoT technologies can be applied in many parts of the construction industry. Some of the applications and a brief explanation are given as follows:

3.5.1.1 Preventive Maintenance:

Embedded systems and sensors in machines monitor any breakdown and report any need for maintenance or repair, especially on-site machines. (Gamil et al., 2020, p. 1093)

3.5.1.2 Reduction Of Admin Expenditure

With data-driven decision-making, administrative expenses can be reduced by producing accurate forecasts and making fast and precise decisions based on the data. (Gamil et al., 2020, p. 1093)

3.5.1.3 Construction Management

In addition to preventing downtime, IoT provides advanced communications with all equipment, such as trucks and materials, allowing decision-makers to reduce excessive consumption of materials and machinery, which could result in cost overruns. (Gamil et al., 2020, p. 1093)

3.5.1.4 Human Resource Monitoring

A labour hour estimate can be tracked using IoT. (Gamil et al., 2020, p. 1093)

3.5.1.5 Safety on Site

In addition to tracking labour on site, IoT also monitors their mobility, allowing any potential hazards to be detected sooner. (Gamil et al., 2020, p. 1093)

3.5.1.6 Just-in-Time (JIT) Provisioning

Supply units can be counted on-site with radio frequency identification (RFID) tags. When a supply unit count drops, a central system requests more supplies. Automated JIT provisioning reduces idle time and helps companies finish construction projects on schedule. Companies will also save money since they will not have to buy supplies that will not be used for a long time. (Volodymyr Rudyi, 2022)

3.5.1.7 Monitoring and Tracking of Tools and Equipment

Tools and equipment can be tracked using IoT technology, reducing the need to replace lost or misplaced items and the time spent searching for them. Landscape equipment fleets with IoT sensors can be tracked using Global Positioning System (GPS) trackers. (Volodymyr Rudyi, 2022)

3.5.1.8 Remote Operations and Activity Monitoring

In addition to remote control and adjustment of machinery, connected measurement sensors and surveillance cameras also enable tracking and reporting of workers' movements and progress and improve accuracy in operation. By doing so, workers' performance is linked to relevant tasks on-site, reducing idle time and helping coordinate building activities more efficiently. IoT-enabled devices provide real-time data, which makes it possible to predict problems at job sites more accurately, as employees are notified when they get closer to certain risks or enter dangerous environments. (Volodymyr Rudyi, 2022)

3.5.1.9 Fuel Saving

Due to the necessity of using machines that consume thousands of dollars per day on large sites, the cost of each construction project corresponds to fuel consumption. Reducing the project's final cost and duration dramatically by controlling expenditures, managing to refuel effectively, ensuring timely maintenance, and upgrading machinery is possible. IoT-enabled fuel sensors can do all of that on construction sites. (Volodymyr Rudyi, 2022)

3.5.1.10 Augmented Reality (AR)

In a construction project, augmented reality can be used in different phases. Construction companies commonly use AR to plan and modify projects, automate measurements, provide onsite project information, enhance team collaboration, and train employees. Using AR, construction firms can create interactive models of their projects by using 2D plans. 3D modelling software allows them to present the models to their clients. Involving clients from the start is an integral part of the process. (Volodymyr Rudyi, 2022)

3.5.1.11 Concrete Curing

IoT-enabled concrete curing sensors can speed up construction schedules. Construction managers can track concrete curing in real time by integrating sensors into concrete during casting. Data is transmitted to the cloud through temperature probes to monitor concrete maturity. Managing the rest of the construction project in this way allows managers to plan precisely. Companies can optimize numerous critical construction tasks by estimating the concrete's compressive strength in situ. It also helps to schedule and cycle formwork and optimize labour where managers can distinguish profitability from loss, allowing them to differentiate loss from profit. (Volodymyr Rudyi, 2022)

3.5.1.12 Building Information Modelling (BIM) and Digital Twins

Engineers can create a digital structure model using BIM software before building construction. As a result, they better understand all the physical and functional nuances of the construction process. Additionally, this software enables builders, engineers, and project managers to identify discrepancies during the initial phases. IoT-enabled devices allow for real-time updates of BIM models, tracking parts, details, or items, and obtaining reports on materials or environmental conditions during construction. Therefore, the BIM model connected to an IoT-enabled sensor will diagnose and analyse the problem when it detects it. Digital twins in construction sync as-built and as-designed models in real-time automatically. A digital tween links real-world objects with their digital representations, which are constantly updated by

IoT-connected sensors. It is collected from physical objects and is then used to represent virtual objects. (Volodymyr Rudyi, 2022)

In conclusion, the Internet of Things (IoT) has enabled the construction industry to monitor, control, and optimize various processes. As a result of integrating sensors, devices, and data analytics, IoT has improved safety, efficiency, and productivity in construction projects. Proactive maintenance and decreased downtime have been achieved by monitoring equipment and machinery in real time and collecting and analysing data. Smart building systems are also possible because the IoT automates lighting, heating, and ventilation. A significant shift in the construction industry has resulted from IoT, which has improved project outcomes and reduced costs.

3.6 Challenges of Adopting AI in Construction

studied the challenges that face the construction industry when implementing the IoT, a summary of those challenges with brief explanations are listed as follows:

3.6.1 Cultural Acceptance of AI

Construction processes are risky and expensive, so even a small mistake can significantly impact. Using traditional methods in construction is preferred *over using* unreliable but new methods that promise big rewards. AI technologies deployed in construction must also be adaptable to different construction sites. Tools need to be thoroughly tested before construction contractors and businesses use them. This may require blockchain technology to increase transparency and trust. Furthermore, most machine learning systems follow a black-box approach, which means they do not explain why conclusions are reached. *For* practitioners to build trust in construction systems, explainable AI (XAI) can produce models that humans can manage, understand, and trust. (Abioye et al., 2021, p. 10)

3.6.2 Data Security

AI can boost security, but hackers, cybercriminals, and intruders can also target it, making the issue significant from an economic and financial standpoint. Construction mistakes can significantly impact quality, cost and time, impacting the overall project plan. Safety compromises can result in life-threatening accidents. AI must fully control or augment construction workers' activities to eliminate security risks. If AI is to be fully controlled or augmented by construction workers, it must eliminate security risks. Therefore, adversarial machine learning (ML) can reduce this risk. In addition to security defence perspectives, adversarial machine learning (ML) is needed for algorithms that resist high-level attacks. The area needs further research, especially for emerging technologies like computer vision and robotics in construction. (Abioye et al., 2021, p. 10)

3.6.3 Lack of Talent

As a result of the many challenges facing the construction industry, it is challenging to find AI engineers with experience in the sector. AI engineers with the needed skills are currently in short supply. Governments can counteract this by increasing spending on science, technology, engineering, and mathematics education (STEM). To create innovations that meet the needs of the construction sector, it is also necessary to collaborate between construction experts and AI researchers. (Abioye et al., 2021, p. 10)

3.6.4 Expensive Initial Investment

AI-driven solutions typically require very high upfront costs and much maintenance. The majority of construction firms and subcontractors cannot afford this. As part of their decision-making process, firms must determine whether such technology will save them money and return on investment. Additionally, as these technologies gain acceptance and ubiquity in construction, they will become more affordable, making them more available to smaller firms. Companies must allocate additional resources to acquire and train employees on artificial intelligence technologies. (Abioye et al., 2021, p. 10)

3.6.5 Powerful Computers and Reliable Internet Access

There is a lack of power, telecommunications, and internet connectivity at most construction sites. This is a severe problem for construction sites whose operations heavily depend on power supplies and internet connectivity, such as robots and site monitoring systems. During construction, for example, when sensors and actuators communicate, it is necessary to compute information in real-time. This issue has been significantly reduced with the use of fourth-generation communication technologies. The fifth-generation communication offers more reliability for construction sites due to its high data rates, reduced latency, energy savings, cost savings, higher system capacity, and massive device connectivity. (Abioye et al., 2021, p. 10)

3.6.6 Big Data Handling

The complexity and lack of understanding of big data make it difficult for organizations to extract data required for specific functions. The selection of data is, therefore, inaccurate because it is extracted from big data; therefore, results or outputs may be incorrect due to the accuracy of the selection. Big data is, therefore, a complex and challenging issue. (Gamil et al., 2020, p. 1094)

3.6.7 Negative Social Impact

With the development of emerging AI technologies, society has significantly changed norms, dramatically transforming how construction industry stakeholders learn, work, communicate and use information. (Gamil et al., 2020, p. 1094)

3.6.8 Safety

Robotics, for example, is too expensive, and their presence in construction sites where they are primarily accessible could be considered a risk for theft. Also, the equipment and tools required to work in IoT are expensive and are mostly exposed. This challenge must be identified before considering implementing AI tools and technologies in construction sites. (Abioye et al., 2021, p. 10)

In conclusion, artificial intelligence in construction has challenges, despite its potential to increase productivity, efficiency, and safety. In order to overcome these obstacles, the construction industry needs to address awareness, integration, cost, data security, and resistance to change. AI adoption in construction can only be successfully achieved if industry stakeholders work together to create an environment conducive to its adoption. Developers must collaborate with industry experts to develop solutions tailored to the industry's needs. In addition, any concerns regarding implementing AI technology should be addressed.

4. Case Studies of Artificial Intelligence in Construction

This chapter introduces five different case studies where the selection was based on the explanation of artificial intelligence branches and sub-branches introduced in Chapter 2 and the analysis of AI involvement in construction in Chapter 3. Table 3 summarises the case studies selection criteria and shows the involved AI technology branch and sub-branch and the use aspect in construction.

AI Branch	Technology	Cost forecasting	Safety Analysis	Report Analysis	BIM	Construction Monitoring	Remote and Adaptable management
Machine Learning	ML						
	DL		CS2				
	ANN	CS1					
Computer vision	CV		CS2				
Natural Language Processing	NLP			CS3			
Internet of Things	IoT						CS5
Robotics	UAVs				CS4	CS4	
	AMRs		CS2				

Table 3 Discussed case studies concerning the AI technology and construction aspect

Table 3 shows the variation in the construction aspects and AI technology discussed in each case study. This diversity illustrates how AI is emerging in different aspects of the construction industry. Case study one discusses the use of ANN in construction project cost forecasting. While the second addressed the use of computer vision and deep learning for safety analysis in construction sites. The third case study discusses using natural language processing NLP to generate reports analysis. Unmanned Aerial Vehicles, especially drones, are discussed in the fourth case study. Together with building information modelling, drones are used in construction monitoring. Finally, in the fifth case study, IoT is used for remote and adaptable management.

4.1 Case Study 1: Use of Artificial Neural Networks for Forecasting

As discussed in Chapter 2, ANN is classified as a part of machine learning. It is a data-driven, self-adapting method based on the underlying assumptions of the model for the problem being studied. They can discover underlying relationships based on examples and their ability to capture subtle functional relationships between data, even if poorly understood. The ANN is thus ideally suited to problems with challenging to specify knowledge but sufficient data or observations to solve them. (G. Zhang et al., 1998, p. 35) The following case study is an example of how ANN could be used in cost forecasting in construction.

4.1.1 Multilayer Perceptron Artificial Neural Networks for Public Construction Cost Forecasting

The case study discussed below developed a computational model based on artificial intelligence to predict the cost of construction projects for Brazilian educational public buildings using artificial intelligence. This study demonstrated that artificial intelligence can be used as an auxiliary construction planning mechanism. The focus is mainly on the ANN algorithms.

4.1.1.1 Background

Brazil does not allow cost overruns in new constructions to exceed 25% (Alcineide et al., 2021a, p. 3). Estimating the actual construction cost can prevent later problems in construction projects and promote better planning. Engineering scholars have also studied the hypothesis raised here. Despite the problem remaining the same in different developing countries, a model's data, training, and results cannot be used confidently in different countries. For example, training a model trained in India may not produce the same results in Brazil, even if they were designed to solve the same problem. (Alcineide et al., 2021a, p. 3)

4.1.1.1.1 Estimating the Cost of Public Construction Projects

During the phases of budgeting, bidding, contracting, and execution of public construction projects, cost forecasting is used to determine whether a particular undertaking is financially feasible. This criterion is unlikely to enable bidders who offer the lowest price to achieve the objectives of a bidding process. By selecting this

option, the quality of the construction will be compromised, and the public administration will experience problems, resulting in taxpayer losses. As indicated in Figure 16, approximately 400 unfinished public works were identified by the Federal Court of Audits Auditor General in 2006, of which 130 were directly developed by the federal government and 270 by states and municipalities. (Alcineide et al., 2021b)

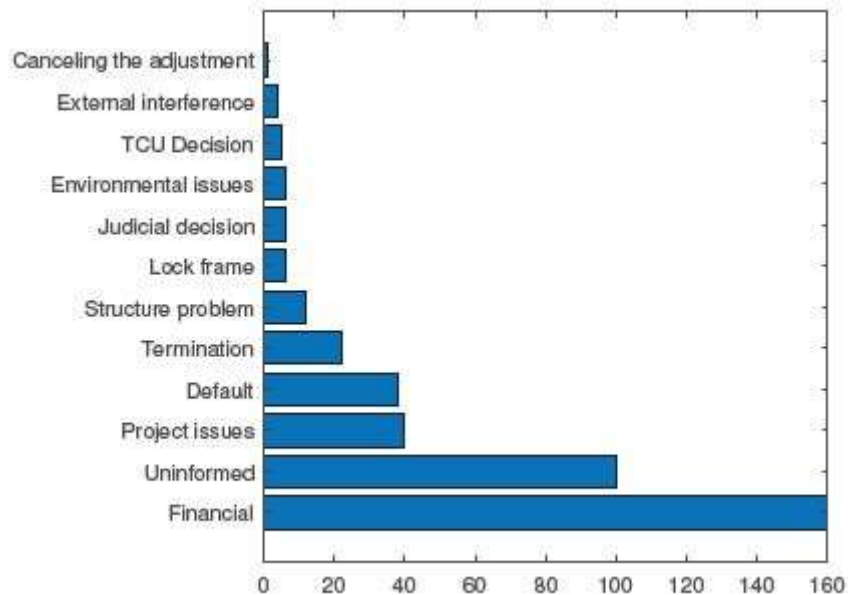


Figure 16 Causes of Work Stoppage (Alcineide et al., 2021b)

A computational model is required to forecast actual costs in the construction market because budgets are an essential factor in stopping public construction projects. (Alcineide et al., 2021b)

4.1.1.1.2 Artificial Neural Networks - ANN

Computer scientists increasingly use artificial neural networks to analyse the nervous system, particularly neurons. Three integral parts are key parts in neuronal communication and information processing: dendrites, cell bodies (or somas), and axons. Synaptic weights, sums, and activation functions are involved in the functioning of an artificial neuron. In Figure 17 below, these parts are arranged in a relationship. (Alcineide et al., 2021b)

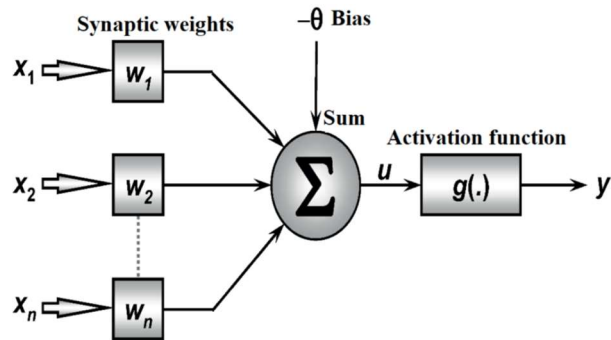


Figure 17 Artificial Neuron (Alcineide et al., 2021b)

The mathematical representation of the Artificial Neuron is represented in Equations 1 and 2.

$$u_k = \sum_{j=1}^m w_{kj} x_j$$

Equation 1 calculation of u (Alcineide et al., 2021b)

$$y_k = g(u_k + b_k)$$

Equation 2 calculation of y (Alcineide et al., 2021b)

Where:

u is the summation of the multiplication of input \mathbf{X} to each synaptic weight.

y is the final estimated value

\mathbf{X} is an input connected to the neuron k in j

\mathbf{W} is the Synaptic weight per each branch

g is the activation function

b is a bias

A multilayer network is defined as having at least one layer between a neural network's input and output layers. The architecture of an ANN is defined as how neurons are arranged together in layers. As shown in Figure 18, the Multilayer Perceptron (MLP) network stands out among these multilayer networks. Multilayer Perceptron networks can solve Several types of problems, such as function approximation, forecasting, and optimization.

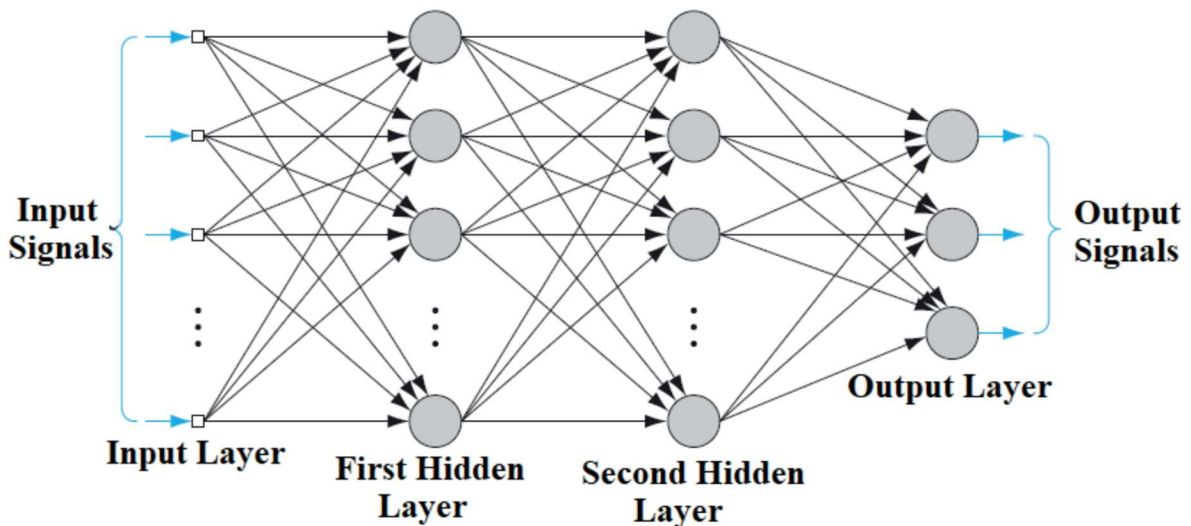


Figure 18 Multilayer Perceptron (MLP) (Alcineide et al., 2021b, p. 3)

Using an MLP network in a given project requires defining its specifications (topology) in advance. Network topology is usually determined by computational tests, which are usually based on the problem at hand. There are several factors to consider when choosing a network topology: input signals, hidden layers, neurons in each hidden layer, and neurons in the output layer. (Alcineide et al., 2021b, p. 3)

Training MLP-type networks involves supervised learning and error backpropagation. There are two phases to a forward-propagation algorithm: propagation and backpropagation. Synaptic weights are multiplied by input signals during this phase. Input signals and synaptic weights are linearly combined to form an activation function, which is then applied to an adder to obtain a linear combination. All neurons and layers are processed until the network output layer is reached. The process is known as backpropagation. Backpropagation starts at the last layer and ends at the first layer. MLP networks operate according to the backpropagation algorithm shown in Figure 19. (Alcineide et al., 2021b, p. 3)

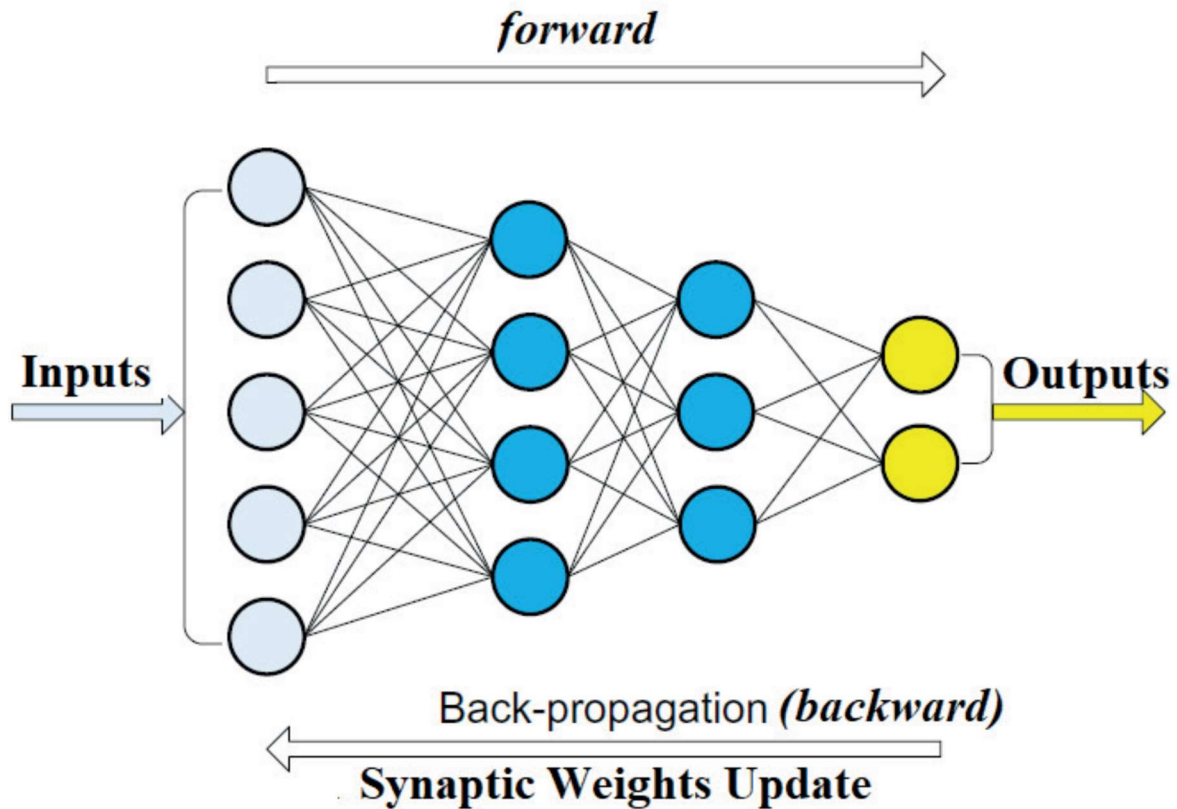


Figure 19 Reinforced Learning using backpropagation (Alcineide et al., 2021b, p. 4)

4.1.1.2 Materials and Methods

Two types of variables must be considered in order to achieve the study's objective. First is a dependent variable, whose value should be predicted when data is lacking. A construction project's final cost was a dependent variable. The second set of independent variables was selected from project characteristics. These independent variables included:

- 1- The size of the facility to be built.
- 2- The number of inspections.
- 3- The estimated budget.
- 4- The contract price.

Information about these variables was selected for projects due to their availability on the Ministry of Education platform (MEC). (Alcineide et al., 2021b, p. 4)

For cost forecasting, the ANN had four inputs, a hidden layer, eight neurons in the hidden layer, and an output (cost). As is depicted in Figure 20, the ANN's topology and training process for cost prediction are shown. The network predicts and

compares a value with the value measured in each loop. The difference in error between one looping and another should therefore be regarded as a criterion for stopping the network.

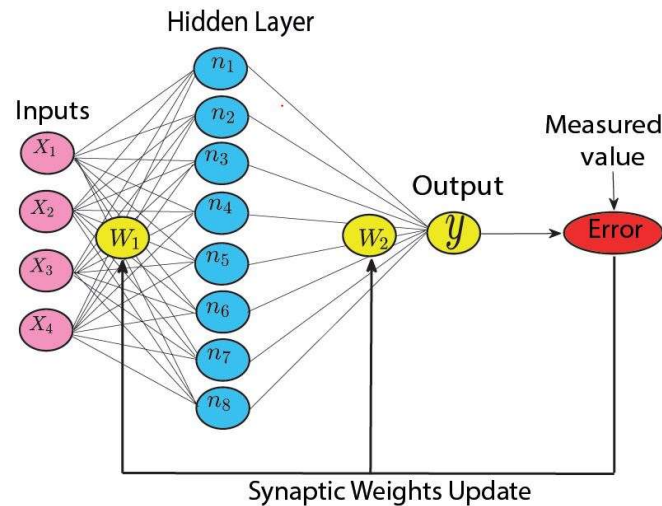


Figure 20 Studying the network topology of the public work cost prediction model (Training)
(Alcineide et al., 2021b, p. 5)

As part of the testing phase, ANNs for cost forecasting are applied only once to new data in the forward phase. In contrast to the training phase, this phase only performs one loop without updating the weight; the weights are used from the training phase, and the calculated error is used to verify the model. Figure 21 shows how an ANN is tested for cost forecasting. (Alcineide et al., 2021b, p. 5)

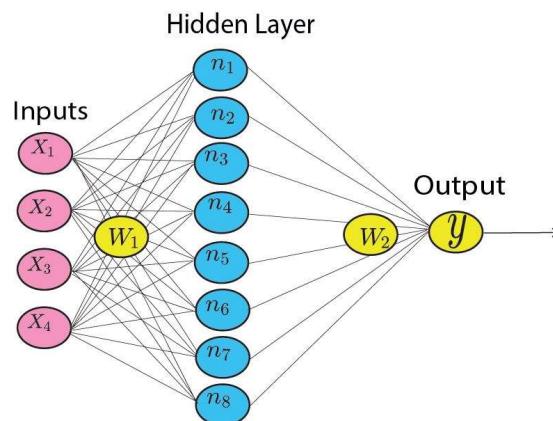


Figure 21 Validation of cost prediction model using network topology (Testing)

(Alcineide et al., 2021b, P. 5)

4.1.1.3 Results

As a result of calculating the outputs of the neural network with actual values, the mean absolute percentage error (MAPE) between those outputs and the actual values was determined. Then a range was determined for cost forecasting based on an upper and lower interval, as shown in Equations 3 and 4.

$$L_s = V_R(1 + MAPE),$$

Equation 3 Upper limit of the assertive range (Alcineide et al., 2021b, p. 6)

$$L_i = V_R(1 - MAPE),$$

Equation 4 Lower limit of the assertive range (Alcineide et al., 2021b, p. 6)

The previously shown equation is constructed as follows: L_s represents the upper limit of assertiveness, L_i represents the lower limit, and V_R represents the real database value. Figure 22 presents a subset of samples to illustrate how the estimated values and the error interval determined in the model analysis are interrelated. However, the estimated values outside the error interval appear to be very close to their upper or lower limits in the presented samples. (Alcineide et al., 2021b, p. 6)

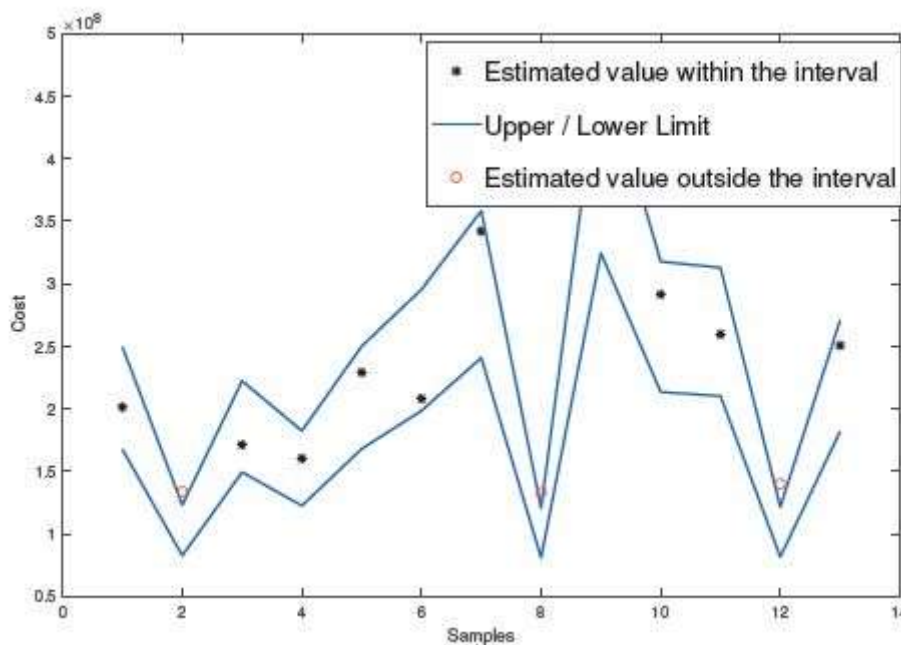


Figure 22 Cost forecasting results from the ANN training phase (Alcineide et al., 2021b, p. 6)

For this phase, 100 samples were separated and used. It is important to note that samples were randomly selected for training and testing. After finding the MAPE

value of 9,14% in the testing phase, an interval to check the model's accuracy was established, similar to what had been done during training. During the testing phase, 90 samples were within this interval, which means that 90% of the samples were accurate. This figure shows which estimated values are within and outside the intervals. Figure 23 shows that almost no values differ significantly concerning the error limits. This suggests that the trained model has a solid ability to generalize. (Alcineide et al., 2021b, . 6)

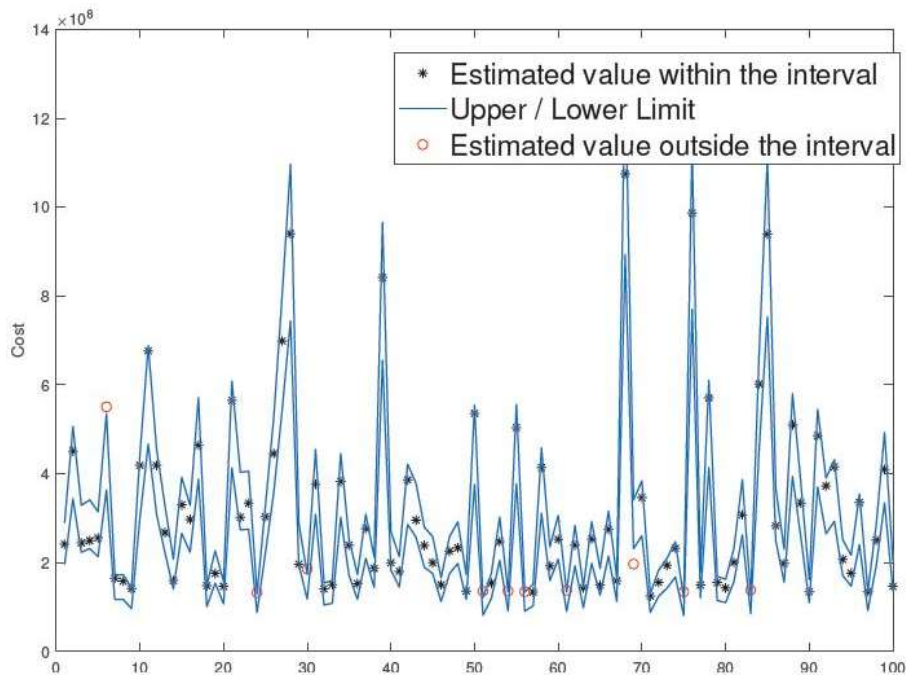


Figure 23 Cost forecasting using ANNs: test results (Alcineide et al., 2021b, p. 6)

4.1.1.4 Conclusion

Public construction projects are often poorly planned, especially in emerging countries, where good planning is crucial to their success. One of the factors attributed to the inefficiency of implementing the plan in this context is the lack of mechanisms for predicting the actual cost of undertakings. A computational model based on neurons was proposed in this case study to provide more credible estimates of the actual values needed for government projects to be completed. In order to collaborate on public construction or renovation projects, such models are most often used. According to the neural model used in the cost forecast, it learned from previous samples and experienced an error rate of 9,14% when applied to new samples, which means that the designed model can predict the final cost of public

sector construction projects with an accuracy of around 90%. (Alcineide et al., 2021b, p. 9)

4.2 Case Study 2: Use of Computer Vision and Deep Learning for Safety Analysis

A basic understanding of computer vision is vital if considered integrated into a company's workflow, as it is a complex topic that requires years of study to comprehend completely. As part of the process, there are three basic steps: data collection, data processing (image processing), and semantic interpretation. First and foremost, a computer must be capable of seeing or, more accurately, acquiring visual information. The computer can collect data in real-time using 2D devices (surveillance cameras, cameras, smartphones, etc.), 3D devices (stereo and Red Green Blue-Depth (RGB-D) technology cameras like Microsoft Kinect), or 3D point clouds (laser scanners). The computer must process data once it has eyes. Thus, the AI will convert the images into a format that can be understood using algorithms such as convolutional neural networks. (Safari AI inc., 2023)

The following case study demonstrates a construction site safety analysis using computer vision (CV) and Deep Learning (DL).

4.2.1 Vision-Based Excavator Activity Analysis and Safety Monitoring System

This case study uses a benchmark dataset from the Autonomous Excavator System (AES) to analyse its performance. A safety monitor and productivity system pipeline using machine vision and deep learning techniques are also presented. This case study integrates detection, pose estimation, and activity recognition modules into the system. Using a general construction dataset, it evaluates the method and produces the best models to achieve the results. However, there are limitations to the current system. (S. Zhang & Zhang, 2021, p. 49)

4.2.1.1 Background

In a real-world environment, excavators operate under extreme conditions, resulting in several fatalities and injuries. In construction sites, safety is a top priority. With advanced deep learning and computer vision technology, the Autonomous Excavator System (AES) can load waste disposal materials into specified areas. The system uses deep learning and computer vision technology. Safety is the primary concern in this case study since the excavator could collide with other construction equipment or the environment. However, even though the system can operate all day without

human intervention, it still warns of potential collisions using cameras that detect excavator poses, the surrounding environment, and other construction machines. (S. Zhang & Zhang, 2021, p. 49,50)

4.2.1.2 Working Framework

A framework for recognizing construction machine activity, monitoring safety, and analyzing productivity is shown in Figure 24 below. Surveillance camera video was used as an input system. The framework consists of six main modules:

- 1- Detection of construction machines
- 2- Estimation of excavator poses
- 3- Segmentation of working areas
- 4- Activity recognition
- 5- Safety monitoring
- 6- Productivity analysis

In order to segment working areas into digging and dumping areas, the surveillance camera video is first segmented. Following that, all construction machines in video frames with their equipment type are identified using the detection method. Secondly, the excavator is identified using pose estimation and detection-based tracking. An excavator's action state is then recognized with pose estimation and segmentation of working areas. Finally, activity recognition and detection results are used to track construction site safety. Moreover, activity recognition results are used to determine the productivity of an excavator, which is described in more detail below in Figure 24. (S. Zhang & Zhang, 2021, p. 51)

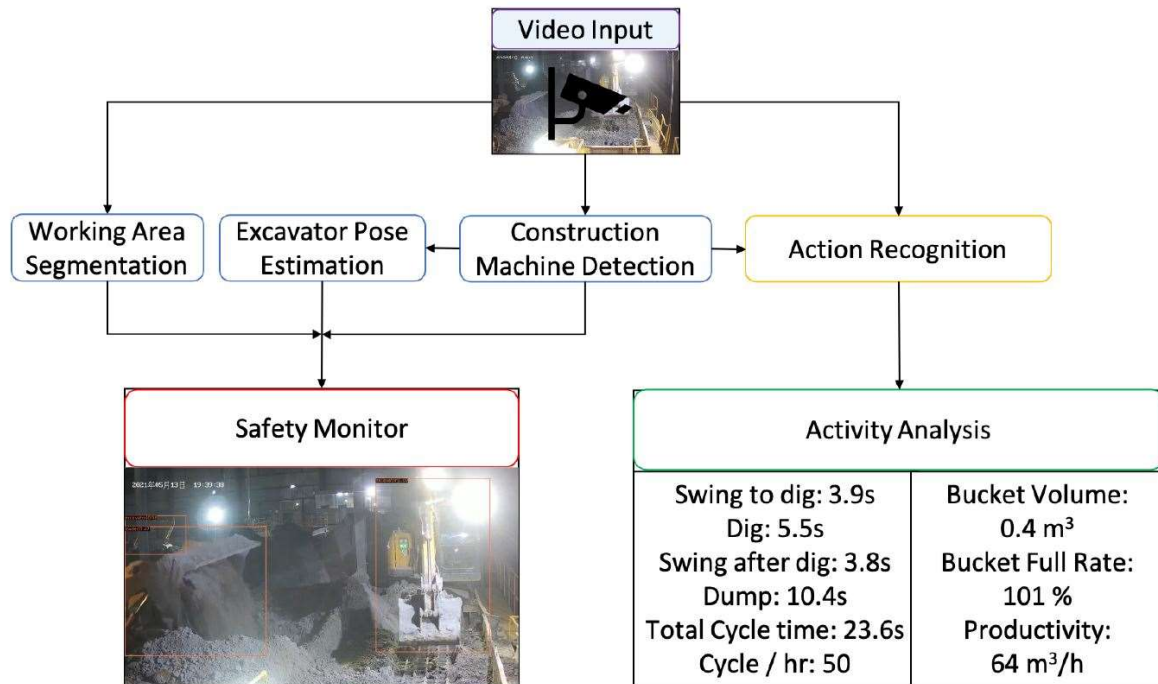


Figure 24 Analysing the activity of autonomous excavators and monitoring their safety. (S. Zhang & Zhang, 2021, p. 50)

As shown in Figure 24, video input processing is divided into work phases. On the one hand, the work area is being segmented according to classification. At the same time the construction machine is detected, the excavation pose is estimated based on that detection. The three modules of detecting the construction machine, estimating the excavator pose and segmenting the working area contribute together to the safety monitor. On the other hand, the construction machine detection and recognising of the action contribute to estimating the activity analysis. (S. Zhang & Zhang, 2021, p. 51)

4.2.1.2.1 Excavators Pose Estimation

There are ten key points on the crawler excavator, which are labelled: two bucket end key points, three bucket joints, two arm joints, four boom joints, and four body points. These points are indicated in Figure 25.

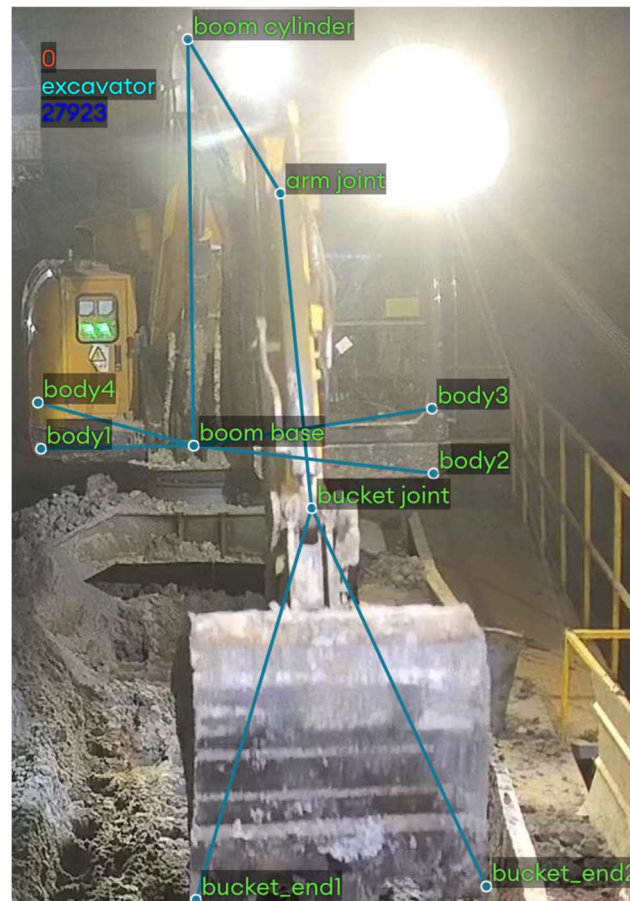


Figure 25 Labels for the positions of the excavator (S. Zhang & Zhang, 2021, p. 51)

Excavators have ten parts that may be identified as key points, including two bucket ends (bucket end1, bucket end2), a bucket joint, an arm joint, a boom cylinder, a boom base, and four body key points (body1, body2, body3, body4). (S. Zhang & Zhang, 2021, p. 51)

4.2.1.2.2 Working Area Segmentation

As illustrated in Figure 26, image segmentation determines digging and dumping areas. In image segmentation, pixels of similar properties are split into multiple segments, each containing pixels of similar properties. Digging areas are designated areas for recycling waste that include various toxic materials. Dumping areas are designated areas for dumping waste. Analysing the colour, texture, and shape of the pixels in an image can be used to determine the digging and dumping areas using image segmentation.



Figure 26 Area segmentation (S. Zhang & Zhang, 2021, p. 51)

As shown in Figure 26, there are two colours, the pink area is dumping, and the blue area is digging. The pink area disposes of excess dirt and other materials, while the blue area is used for excavating and extracting resources. Waste and debris generated during excavation are stored in the pink area, whereas the blue area is usually a quarry where minerals, metals, and other resources are dug out from the ground.

4.2.1.2.3 Excavator Action Recognition

Excavator actions are as follows:

1. The digging process
2. The swinging motion
3. The act of dumping

On the other hand, the autonomous excavator has four states:

1. The state of the digging
2. The swinging motion after digging
3. The state of the dump
4. The swinging for digging state

Excavator buckets are loaded with target material when digging; excavator buckets are swung after digging to dump the material; when dumping, the material is unloaded, and when digging, the bucket is swung to the working area. Furthermore, there is an optional idle state when the excavator is manned or malfunctioning. Using pose estimation and image segmentation results, firstly, the excavator position to

determine the excavator action state is determined, then it is determined whether the excavator is in swing by using continuous frames of pose key points of bodies 1-4. The safety monitoring system uses a rule-based module that measures pose key points for each movement on the body 1-4. If these key points are smaller than a set value, the excavator body is considered still. If they are not, then the excavator body is not still. (S. Zhang & Zhang, 2021, p. 52)

The following are the excavator action states:

1. An excavator body is stilled with buckets, arms, and body 1-4 fixed in the digging area.
2. A swinging state consists of bucket/arm joints in the working area, and body 1-4 is not still (excavator body is not still). It can then be determined whether it is a swinging state or a swinging state after the digging state based on the previous state. If the previous state is dumping, it is a swinging state. Otherwise, it will be a swinging state after digging.
3. In idle state, buckets/arm joints/bodies 1-4 are stilled (excavator arm and body both stilled), and buckets/arm joints/bodies 1-3 are in the dumping area.
4. In idle state, buckets/arm joints/bodies 1-4 are stilled (excavator arm and body both stilled), and buckets/arm joints/bodies 1-3 are in the dumping area.

4.2.1.3 Construction Machine Safety Monitor (Detection of Potential Collisions)

A potential collision between the autonomous excavator and the loader is essential because the loader does not know which state the excavator is currently in from his viewpoint. Autonomous vehicles may be halted until the issue has been resolved if more than one machine is found in the same area (digging or working area). An alert may be displayed if multiple machines are found in the same area. (S. Zhang & Zhang, 2021, p. 52)



Figure 27 The autonomous excavator and loader potential (S. Zhang & Zhang, 2021, p. 52)

As shown in Figure 27, the autonomous excavator and loader can collide when the loader tries to load in the digging area. In this case, a danger signal will be sent when both machines are detected.

4.2.1.4 Conclusion

The discussed case study showed how computer vision can contribute to the construction industry. It showed the potential of using such technology to enhance safety analysis and introduce preventive methodologies to avoid accidents in construction sites. The framework of computer vision and how cameras can understand the construction environment were explained. Autonomous Excavator Systems are evolving into the industry, and using such technologies gives more guarantees about their performance and how reliable they could be regarding productivity, profitability, and safety.

4.3 Case Study 3: Use of Natural Language Processing in Analysing Reports

Natural Language Processing (NLP) can facilitate project management and engineering information management in the construction industry by deeply examining many text files accumulated in the construction industry. In construction, NLP is becoming increasingly popular for improving safety because it retrieves key information from safety reports and conducts content analyses to make construction safety reports more interpretable and reduce ambiguity. It is common for safety reports to include detailed information, such as dates, times, locations, causes, and injuries, as well as unstructured or semi-structured data that documents undesired construction incidents. Using natural language processing (NLP), managers can efficiently extract many unstructured textual reports, helping them learn from incident precursors and control and assess construction safety more effectively. As a result, human intervention can be carried out in time to reduce risk on construction sites and procedures. The process is accomplished by identifying and classifying dangerous behaviours and factors as early as possible to analyse them post-event.

Further, it can predict future hazards, such as worker injuries and deaths, equipment damage, abnormal processes, or conditions. Managers can take proactive measures to prevent such incidents. (Pan & Zhang, 2021, p. 10)

4.3.1 Natural Language Processing and Text Mining for Construction Site Accident Analysis.

It is crucial to analyse accidents to prevent similar accidents in the future and to develop scientific risk control strategies. Construction accidents cause human suffering and massive financial losses in many countries. Text mining and Natural Language Processing have been used in this study to develop five baseline models for classifying construction accidents. It is possible to use support vector machines (SVMs), linear regression (LRs), K-nearest neighbours (KNNs), decision trees (DTs), Naive Bayes (NBs), and ensemble models to analyse data. In addition, the proposed approach is more robust when low support is present. (F. Zhang et al., 2019, p. 238)

4.3.1.1 Background

Approximately 2.78 million deaths occur every year as a result of occupational accidents in the construction industry worldwide, according to the International Labor Organization (ILO). In addition to causing severe health problems, construction accidents also result in substantial financial losses. Analysis of past accidents is crucial in preventing similar accidents and promoting workplace safety. Safety professionals can take appropriate actions based on cause analysis results to eliminate or reduce the identified causes. After identifying such causes, mitigation strategies can be developed. These strategies include raising awareness and performing mandatory regular checks to prevent accidents from recurring. (F. Zhang et al., 2019, p. 238)

4.3.1.2 Text Mining and Natural Language Processing

Text Mining involves identifying information from text data that was previously unknown and difficult to discover. Several areas of artificial intelligence, computational linguistics, mathematics, and information science are used to perform Natural Language Processing (NLP). In NLP, natural language is understood by computers and specific tasks are performed. This approach can analyse text's semantics and grammatical structure, which cannot be accomplished by text mining alone. (F. Zhang et al., 2019, p. 239)

4.3.1.2.1 Ensemble Model

A process of ensemble model uses many different modelling algorithms and training datasets to create a variety of models in order to predict a particular outcome. In Figure 28, there are several steps with sub-steps and all together form the ensemble model. Those steps are Data processing, preprocessing, Model Building, Weights optimization and Voting. Figure 28 shows the workflow of the ensemble model. (F. Zhang et al., 2019, p. 242)

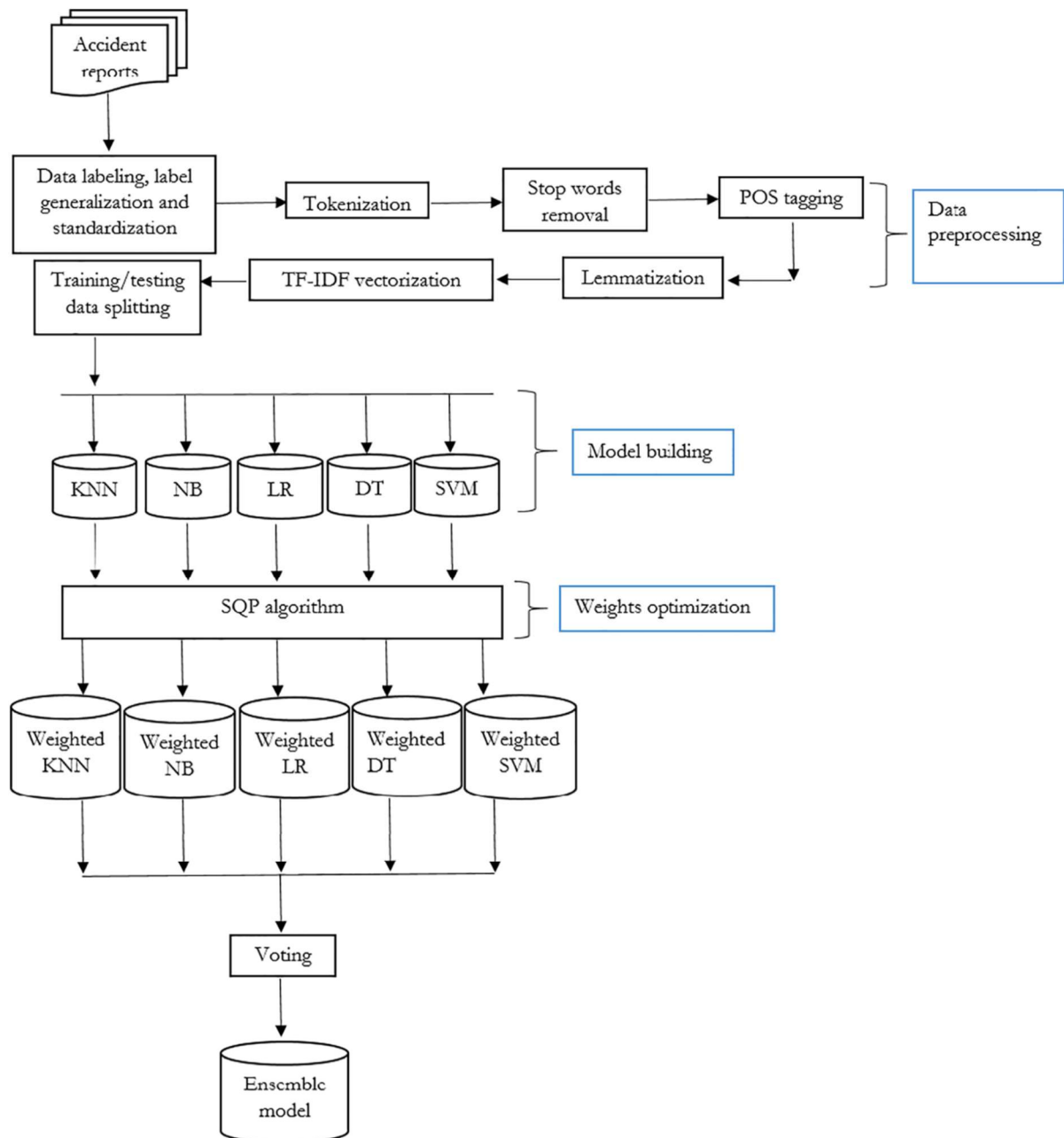


Figure 28 Workflow of the ensemble model. (F. Zhang et al., 2019, p. 240)

The workflow illustrated in Figure 28 is explained in detail as follows:

4.3.1.2.2 Data Preprocessing

Several steps are required before classifiers can be applied to text data, including preprocessing and feature extraction. The following steps are commonly used to process text:

- 1- **A lowercase and punctuation removal step:** This step reduces variation in the same word by transforming it into lowercase. For example, "Employee" and "employee" are treated similarly after transformation. In most cases,

punctuations do not contribute much to text analysis and increase training data, so they are removed. (F. Zhang et al., 2019, p. 239)

- 2- **The use of stopwords:** Using stopwords in document selection is ineffective because they are widespread words. Typical stopwords in medical documents are 'pill' and 'patient', while those in computer products documents include 'CPU' and 'memory'. Often, common stopwords do not cover specific terms, so that a domain-specific stopword list can be created. (F. Zhang et al., 2019, p. 239)
- 3- **Tokenization:** By tokenizing sentences, programs can work with them as understandable data chunks. In tokenization, certain characters, such as punctuation, are filtered out while chopping up a character sequence and document unit into pieces, called tokens. Figure 29 gives an example of tokenization. (F. Zhang et al., 2019, p. 239)

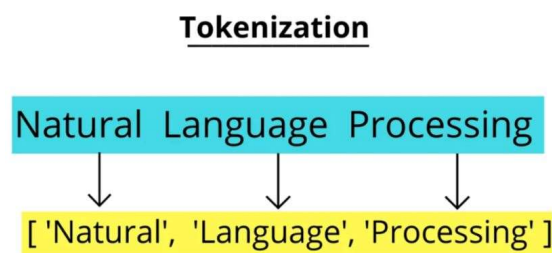


Figure 29 Tokenization (Khanna, 2022)

- 4- **Stemming and lemmatization:** The same word can be expressed differently in a document, such as 'kill', 'kills', and 'killing'. In addition, words can have different syntactic categories based on their root forms and semantic association, such as 'irony' and 'ironic'. There are two grammatical reasons for the two mentioned scenarios. In order to reduce an inflectional form or derivationally related form of a word, stemming and lemmatization are used. For example, converting 'am', 'is', and 'are' to 'be', converting 'dog', 'dogs', and 'dog's' to 'dog'. (F. Zhang et al., 2019, p. 239)
- 5- **Part of Speech tagging (POS tagging):** This step assigns an assigned tag to each token, including nouns, verbs, and adjectives. (F. Zhang et al., 2019, p. 239)
- 6- **N-grams:** Typically, n-grams are composed of co-occurring words within a given window size, i.e., n is one, two, or three for unigrams, bigrams, and trigrams. For example, in the sentence 'he is a boy', unigrams include 'he', 'is',

'a', and 'boy', while bigrams include 'he is', 'is a', 'a boy' and trigrams are 'he is a', 'is a boy'. (F. Zhang et al., 2019, p. 239)

7- Term Frequency – Inverse Document Frequency (TF-IDF): TF-IDF is an approach that emphasizes the importance of high-frequency words within one document over words frequently appearing in many documents. (F. Zhang et al., 2019, p. 240)

4.3.1.2.3 Model Building

The ensemble model is proposed to improve the conventional majority voting-based mechanism by optimizing the weights of the ensemble model, utilizing the Sequential quadratic programming (SQP) algorithm to optimize the Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Decision Tree (DT), Logistic Regression (LR), and Naive Bayesian (NB) classifiers. The previously mentioned five algorithms are summarized in Table 4.

Algorithm	Name	Use
SVM	Support Vector Machine	- Solve the optimization problem - Risk minimization
KNN	K-Nearest Neighbour	- Pattern classification based on feature similarity
DT	Decision tree	- Hierarchical tree-based classifier
LR	Logistic regression	- Describe the relationship between a response variable and other explanatory variables.
NB	Naive Bayesian	- text categorization tasks - probabilistic classifiers - family
SQP	Sequential quadratic programming	- solving constrained - nonlinear optimization problems

Table 4 Used Algorithms for Model Building (F. Zhang et al., 2019, p. 241,242)

4.3.1.3 Ensemble Model and the proposed approach

A composite classifier improves robustness and generalization over a single classifier by combining the results of several base classifiers, which are generally weak classifiers. As a result of the training process, the total bias is reduced when the base classifiers are built sequentially, and the weak learners of the last round are given more weight to misclassified data. To classify accident causes, this case study

combines the five single classifiers outlined above (see Table 4). Moreover, the SQP algorithm is utilized to optimize the weight for each base classifier instead of assigning equal weight to each base classifier for majority voting. (F. Zhang et al., 2019, p. 242)

4.3.1.4 Experiments and Results (Training)

A classifier is developed for the mentioned case study to classify the cause of construction accidents. A free version of the Occupational Safety and Health Administration (OSHA) sponsored dataset is available for download. It contains 16,323 records of accidents at construction sites (happening between 1983 and 2016) but does not specify their cause. In addition to causal factors and events that contributed to the incident, the report provides a detailed description of the incident. For classification in this study, case summaries are used. (F. Zhang et al., 2019, p. 245)

4.3.1.4.1 Accident classification

As shown in Table 5, a sample case is annotated based on Workplace Safety and Health Institute (2016) labels. To avoid having multiple categories for a case, if more than one incident leads to an accident, then the first incident is assigned the label.

Title	Firefighter dies after being struck by collapsing wall.
Summary	On June 17 2011 Employee #1 a volunteer firefighter with the Du Quoin Fire, Department was fighting a fire in a brick structure. He was wearing full turnout gear. While Employee #1 and another firefighter were removing a 35 ft. extension ladder from the side of the building its second story collapsed. Bricks struck Employee #1's head and neck. He was transported to a hospital where he died later that day. The second firefighter was not injured.
Cause (manually labelled)	Collapse of object

Table 5 Sample Labelled case (F. Zhang et al., 2019, p. 241)

The sample case shown in Table 5 is labelled as "Collapse of object" because the first incident was "second story collapsed", and the second incident was "Bricks struck Employee #1's head and neck". To reduce the number of labels representing similar causes, the cases are annotated in a more general and standard manner. In Table 5, the cause of the case is labelled "Collapse of an object" rather than "Collapse of a building story". As a result, the dataset is labelled with 11 accident causes: "caught in/between objects", "collapse of object", "electrocution", "exposure to chemical substances", "exposure to extreme temperatures", "falls", "fires and explosions", "struck by moving objects" "struck by falling objects", "traffic", and

“others”. The distribution of those 11 is indicated in Figure 30. (F. Zhang et al., 2019, p. 246)

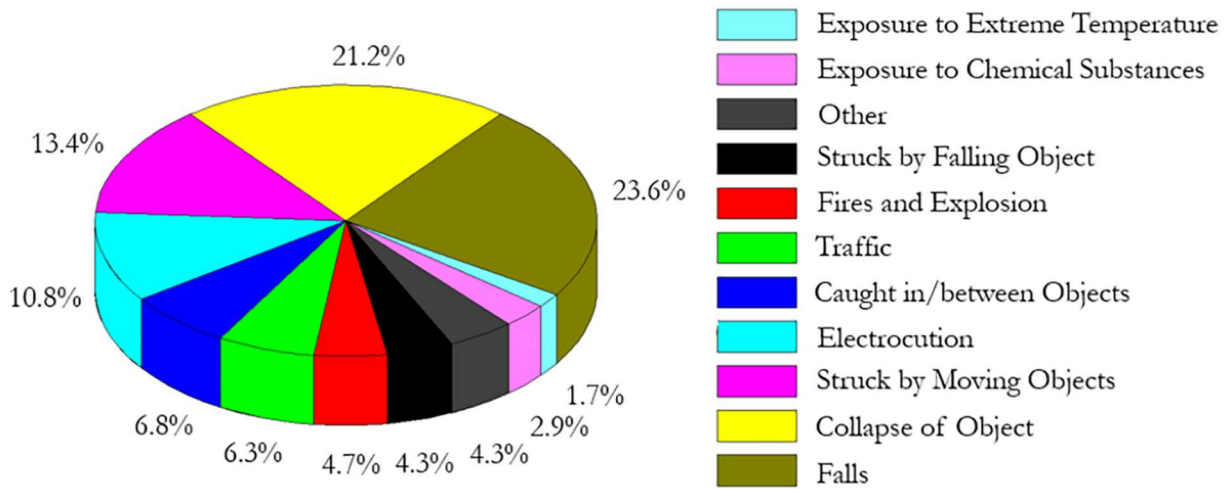


Figure 30 Distribution of the different causes of accidents. (F. Zhang et al., 2019, p. 242)

Figure 30 shows the distribution to give a share of 23.6% for falls, where collapsing of an object is 21.2%. Furthermore, the struck by moving objects is 13.4%, and electrocution is 10.8%. Other causes range below 10%.

4.3.1.5 Conclusion

Analysing the construction accident reports leads to valuable knowledge of what went wrong in the past in order to prevent future accidents. With the help of NLP, it was possible to analyse over 16 thousand records of accidents at construction sites and identify the different causes of accidents, as shown in Figure 30. Accident causes classification is essential as prevention strategies should be developed based on different causes accordingly.

4.4 Case Study 4: Use of Robotics in Construction Management

Construction is a recent application of drones, although they have been frequently used in other industries (agriculture, public safety, military purposes, science and research, monitoring security, and mining). Among the many applications of aerial vehicles in the construction industry are inspections of highways, bridges, roads, cell towers, high mast lighting, wind turbines, power lines, façades and roofs, surveying and mapping, construction monitoring, wetland and environmental monitoring, drainage and erosion monitoring, traffic monitoring, and emergency services. With its wide view of inaccessible and otherwise difficult and hard-to-navigate areas, UAVs provide invaluable help and cost savings. With the overhead perspective and 360° panoramas, UAVs provide real-time insight into the best access. Informed by this information, engineers can prioritize their approaches. Operators can share imaging with on-site staff, internal personnel, and external subcontractors. Using photogrammetry techniques, drone images and point clouds (from 3D scanning of construction sites) can be used to build 3D models. The construction progress can be monitored by comparing the drone and BIM models at various stages. Aside from scheduling and costing for the construction project, this comparison can also include real-time recording, reporting, billing, verification, and planning. (Tkáč & Mésároš, 2019, p. 27)

In the following case study, drones and unmanned aerial vehicles (UAVs) are introduced in construction to monitor and report the progress.

4.4.1 Construction Monitoring and Reporting Using Drones and Unmanned Aerial Vehicles (UAVs)

The construction industry can benefit from drones and UAVs in virtually all practical aspects, including construction planning and monitoring. Drones and UAVs can significantly improve performance and speed in many areas. Drones and unmanned aerial vehicles can preplan construction projects, conduct detailed surveys, map projects, monitor the construction process, and conduct post-build inspections. Planners can also use drones to monitor whether their construction projects are aligned with their vision in real-time. In addition to tracking inventory and planning the

entire construction site, drone data can also be helpful to developers and construction firms. (Anwar et al., 2018)

4.4.1.1 Background

As a result of real-time data obtained from drones and drone-assisted unmanned aerial vehicles, this case study presents a framework for developing a smart construction monitoring and reporting system. The key steps in traditional construction monitoring and planning are illustrated in Figure 31. Conventional monitoring approaches construct BIM models from construction drawings to plan the construction sequence and monitor the progress. (Anwar et al., 2018)

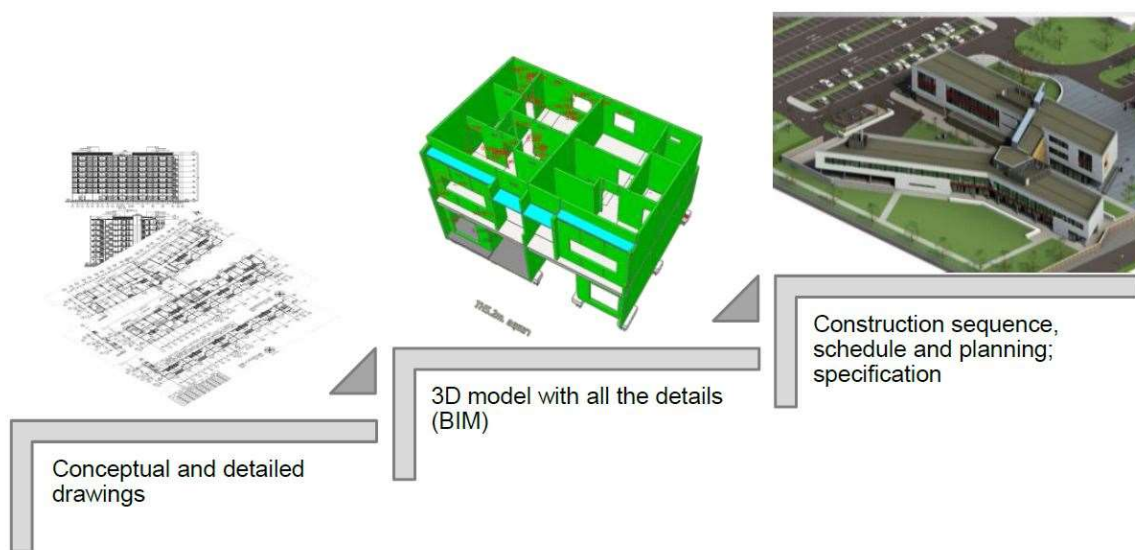


Figure 31 Planning and monitoring construction traditionally involves a few key steps (Anwar et al., 2018)

As part of the presented approach, drone and UAV images from multiple locations and point clouds (from 3D scanning of construction sites) are used to construct a 3D model using photogrammetry. Several stages of an example construction project can be demonstrated using a sequence of 3D models in Figure 32, which compares it to a BIM model at various construction stages. (Anwar et al., 2018)

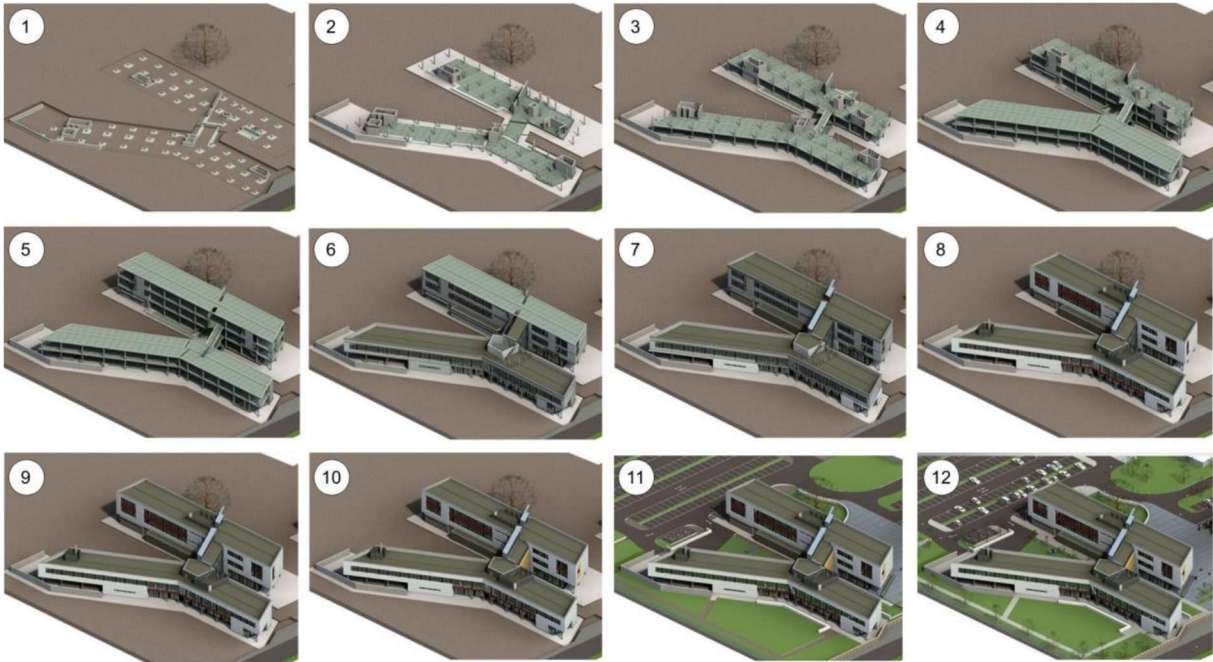


Figure 32 An interactive 3D model illustrates the various phases of a construction project.

(Anwar et al., 2018)

After introducing the construction planning and monitoring different key steps and the three-dimensional model of different phases of construction, the following section explains the smart version using drones and UAVs. (Anwar et al., 2018)

4.4.1.2 The Use of Drones for Monitoring a case study project

An example of smart construction monitoring is shown with a construction project for a single-story apartment building. Drones were used to monitor construction activities continuously. Drones have flown at least four times during different stages of construction to capture various data based on their height and camera angle. At approximately 30 meters above the height of the case study building, the camera was angled at 0 degrees for the first data set. In the second data set, the drone was flown at an angle of 80 degrees at an approximate distance of 20 meters from the building height. To obtain the third data set, the drone was flown at an angle of 45 degrees at 30 meters above the building height. In order to collect the final data set, the drone must be flown at an angle of 30 degrees at approximately 50 meters altitude. (Anwar et al., 2018)

A 3D model was generated after aerial photography. After the 3D model is generated, it is exported as a .obj (Wavefront) file. "3DF Zephyr" software was used for the 3D reconstruction. To compare the different dimensions of buildings, the data is imported into REVIT and then overlaid with the actual REVIT models. Various

comparisons were conducted using this overlay at different construction project phases. The following are potential outcomes of the drone-based construction monitoring approach presented here:

1. Cost savings
2. Schedule Comparison
3. High-quality design and construction
4. Completed projects much more closely aligned with the design intent
5. Elimination of the need for separate as-built drawings

Using the selected case study project as a model, the volumetric comparison between the construction plan/schedule and on-site progress can be seen in Figure 33. It is possible to monitor the project's progress with reasonable accuracy by comparing the BIM model (red colour) with the drone model (green colour). The project can be benchmarked and monitored with various targets and benchmarks. In addition, comparisons can also be made at different stages of the project. (Anwar et al., 2018)

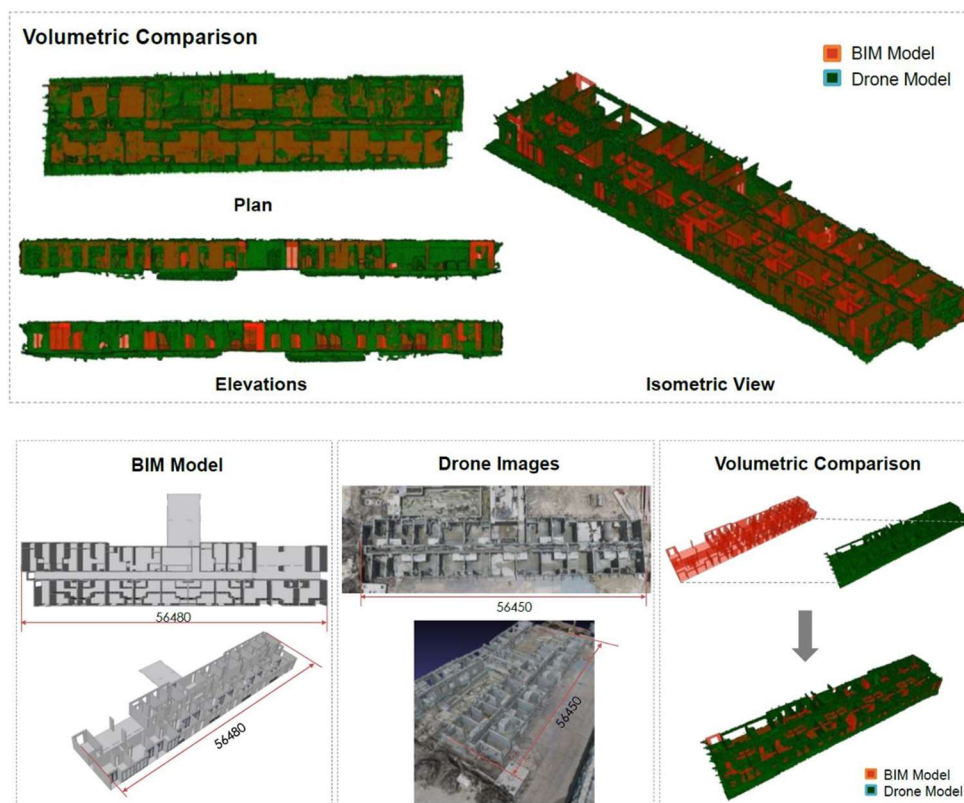


Figure 33 Comparison of volumes between construction plans and schedules and progress on the site (Anwar et al., 2018)

Figure 34 shows an example where the placement of toilets is on a schedule based on the quantity of toilets shown.

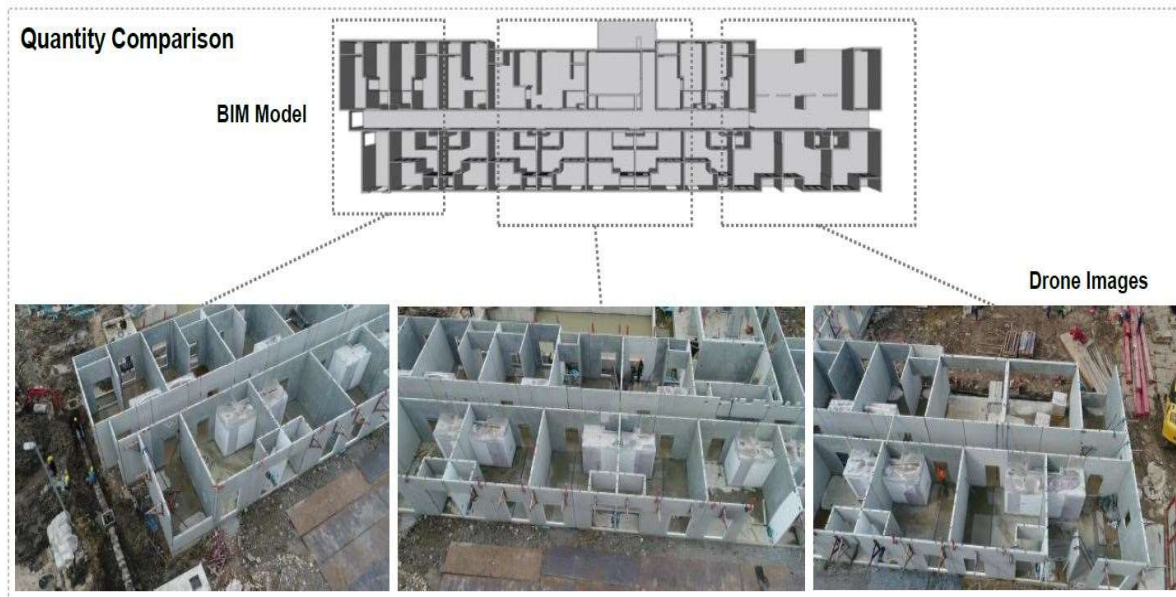


Figure 34 The placement of toilets is on schedule, as illustrated by the following example quantity comparison (Anwar et al., 2018)

As in Figure 34, Figure 35 shows an example schedule comparison for the placement of windows in the case study project. This case study illustrates the effectiveness of the presented approach for smart monitoring of construction projects by demonstrating that the placement is delayed by schedule. (Anwar et al., 2018)



Figure 35 The placement of windows is delayed due to schedule delays in the case study project.

(Anwar et al., 2018)

The presented technique was applied to five other case study buildings to assess its accuracy and compared to actual data for five other buildings. It has been observed that the drone 3D models are reasonably consistent in shape and geometry of the actual building dimensions compared to measurements of the buildings in the case study. However, data source, data quality, drone height, camera angle during image capture and construction methods can all contribute to certain types of errors. It was found that the mean error is less than 0.12 meters in the measurements of the control points for the five cases tested. (Anwar et al., 2018)

4.4.1.3 Conclusion

It is demonstrated that drone data can be effectively used to monitor construction projects and can be compared with BIM models. The required effort can be significantly reduced by fully automating the construction monitoring and reporting process. The system provides convenient and smart site supervision and management, resulting in better operations, planning and effective on-site adjustments. (Anwar et al., 2018)

4.5 Case Study 5: Use of Internet of Things for Construction Project Analysis

As the size and budget of significant civil engineering projects increase (e.g., highway construction), they become increasingly complex and challenging. Managing and coordinating such complex projects is not an easy task. As a result, project managers must frequently or even permanently be physically present, as in many cases, data is either non-existent or sparse and incomplete. In addition to slow reporting and manual ad hoc information collection processes, information availability on-site is severely limited. Several processes are not tracked at all or are only reported using paper-based document sheets. Smart Construction is proposed to resolve this issue and increase the efficiency and predictability of large construction projects. An Internet of Things (IoT) cloud-based platform allows dynamic and adaptable applications to be built and managed in construction sites. (Bucchiarone et al., 2020, p. 38) The following case study is an example of how IoT would be beneficial in the area of construction management.

4.5.1 Managing Construction Sites Remotely and Adaptively with IoT

The need for a project manager's presence on-site is almost permanent due to the lack of reliable digital data. Managing and coordinating complex projects is a difficult task. However, they still have to gather information manually and slowly on-site. This case study discusses using Smart Construction, an Internet of Things cloud-based platform, for large civil engineering projects. In order to adapt their operations based on real-time data analytics results, project managers can remotely manage multiple construction sites in multiple locations at once through the platform. For two experiments, the platform collects real-time data from real construction sites under realistic conditions. (Bucchiarone et al., 2020, p. 38)

4.5.1.1 Background

The earthwork phase of highway construction is examined as part of investigating the proposed solution. One of the main activities is transporting fill material from the excavation to the construction site and spreading and compacting it until the layers meet the required quality. Moving the excavation zone closer to the construction site often shortens transport times. As fill material is spread by bulldozers and compacted

by road rollers at the construction site, the goal is to ensure a steady supply. To achieve efficiency, this task must be performed with minimal backup capacity and fine-tuned resource utilization (e.g., fewer vehicles per route, closest excavation zone). (Bucchiarone et al., 2020, p. 39)

During the earthwork phase, there are typically four types of problems:

- Bulldozers and rollers at the construction site are idle because of insufficient fill material. More trucks, routes, or closer sources might be used as a solution.
- There is a queue for truck loading and so trucks sit idle while waiting. Adding more excavators or changing excavation zones might reduce waiting times.
- Using more trucks on the route could increase the transfer capacity since excavators spend more time idle when there is no truck to load.
- It is essential to consider alternative routes or excavation zones if unexpected delays occur on the transfer route, for instance, due to poor road conditions.

During the requirement collection phase, construction site managers pointed out that in many available solutions, coordination occurs ad hoc as one or more project managers react to operator reports. Individual operators observe, report, and project managers apply their skills as part of this process. The manual process can also slow things down since coordinators cannot react to problems until they have already occurred. (Bucchiarone et al., 2020, p. 39)

4.5.1.2 Smart Construction Platform

Construction projects run more smoothly and efficiently when workflows and procedures are integrated across multiple actors (e.g., workers, drivers, and project managers). Based on the variability of construction site procedures (highway and bridge construction), the platform can handle both the scenario's dynamic aspects and the contextual changes. The platform can dynamically instantiate different workflows using different available resources to specialize them in specific contexts. In addition to the selected construction site, all necessary (contextual) data (e.g., truck speeds, bulldozer, truck, roller status, fill material quantity) is matched. If a problem is detected, a workflow adaptation proposes alternative procedures to the involved parties. On-site IoT networks with appropriate, configurable smart nodes are deployed on construction sites as part of the platform, while the backend cloud

platform with a user-friendly interface is deployed in the backend. Figure 36 illustrates the relationships among the high-level components. (Bucchiarone et al., 2020, p. 39)

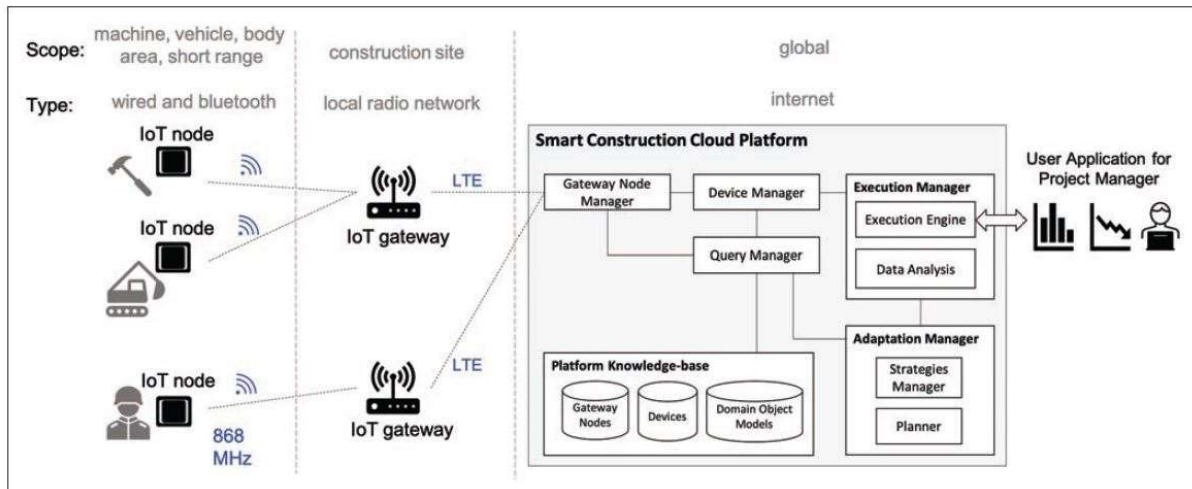


Figure 36 An overview of the Smart Construction platform from a technical perspective

(Bucchiarone et al., 2020, p. 40)

The local radio network collects and distributes information between smart hardware nodes distributed across the construction site. The system is connected to the cloud platform via IoT gateways (mobile or wired connection) via the Internet (mobile or wired connection). The web-based user application enables project managers to access information from anywhere. Figure 36 depicts, in particular, the main components of Smart Construction's cloud platform with their connections. Managing the gateway nodes distributed across the different construction sites is the responsibility of the Gateway Node Manager, which is responsible for accessing the platform. The platform Gateway Nodes database records each gateway node as a tuple comprised of two keys and one signature. In addition to handling gateway authentication during the execution phase, the Gateway Node Manager only accepts information from gateway nodes with a valid key signature entry. (Bucchiarone et al., 2020, p. 40)

4.5.1.3 User Interface for Project Managers

In order to handle any upcoming issues on the construction site, this platform is geared toward personnel responsible for ensuring the efficiency of the construction site. From a desktop computer or mobile device, the platform provides real-time information, notifications, and current and historical statistics to help them make the right decisions. Figure 37 shows two snapshots of the User Application Interface implementation. (Bucchiarone et al., 2020, p. 41)



Figure 37 Screenshot of the user interface dashboard (Bucchiarone et al., 2020, p. 42)

Figure 37 shows how the user interface is displayed to identify potential delays and take corrective action, and the project manager receives a real-time overview of each tracked vehicle's state, location, and activities. Additionally, it ensures that resources are allocated to the right places at the right time to maximize efficiency and minimize costs. Figure 38 shows data and statistics displayed in this screenshot of the user interface dashboard over the last week. In order to inform decisions, the data can be used to identify areas for improvement. The metrics are divided into categories, including accumulated production in cubic meters, daily trips, and cycle statistics.

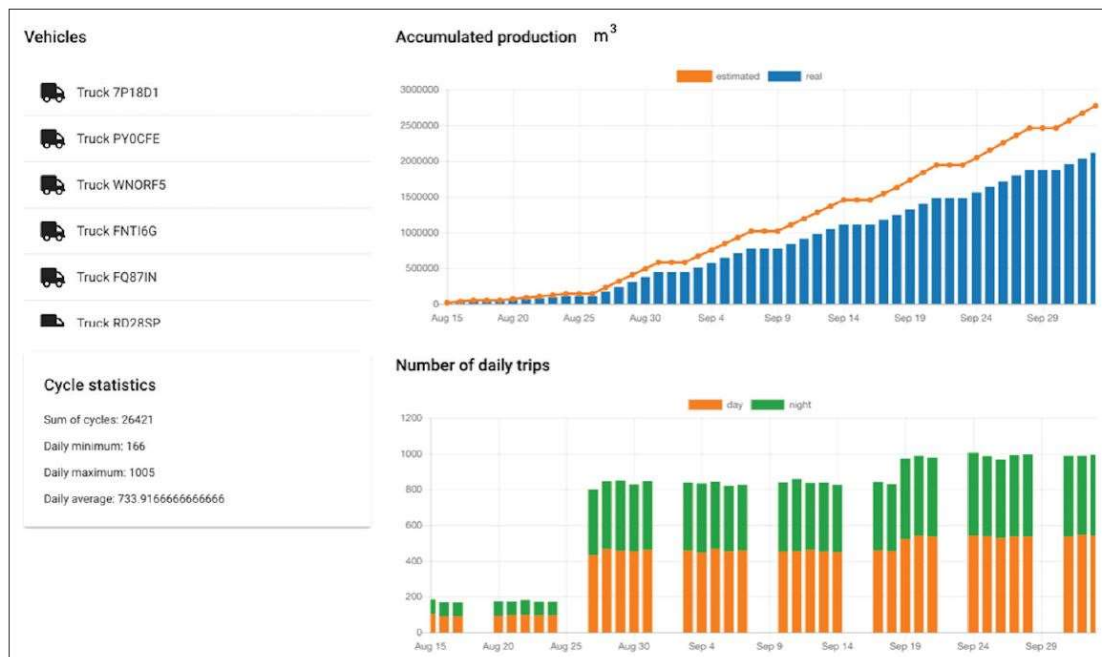


Figure 38 Data and statistics over the last week are shown in this screenshot of the user interface dashboard (Bucchiarone et al., 2020, p. 43)

Through the real-time data provided in Figure 38, a project manager can check the productivity of machinery and compare it to benchmarks. For example, a comparison between the night and morning shifts could be performed, which would be used to run a cost-benefit analysis to check the profitability of the night shift.

4.5.1.4 Construction Site Tests

From seven in the morning to two in the afternoon, sensor data was collected from all four trucks and one excavator working on two different transportation routes. Although the data from the first site showed similar characteristics, mainly the data from the second construction site was used for data inspection. Figure 39 shows the smart node and the location of installation to the machinery to monitor them. (Bucchiarone et al., 2020, p. 42)



Figure 39 Left: picture of the smart node; right: smart nodes are installed to the vehicles
(Bucchiarone et al., 2020, p. 43)

Figure 40 represents data collected and analysed from construction sites. It is divided into four parts as follows:

- a) A frequently travelled route is shown on the upper right, while two variants are also shown on the lower left.
- b) The following timeline shows the durations of the cycles for each truck over the morning shift. Observe that longer cycles on a specific route be clustered together in time. Trucks 1 and 4 mostly travelled Route 1, while trucks 2 and 3 mostly travelled Route 2.
- c) In Figure C, the duration times are shown by the route.

- d) Based on vehicle position and speed, a simple decision tree classifier is used to extract the different activity states of the vehicles automatically.

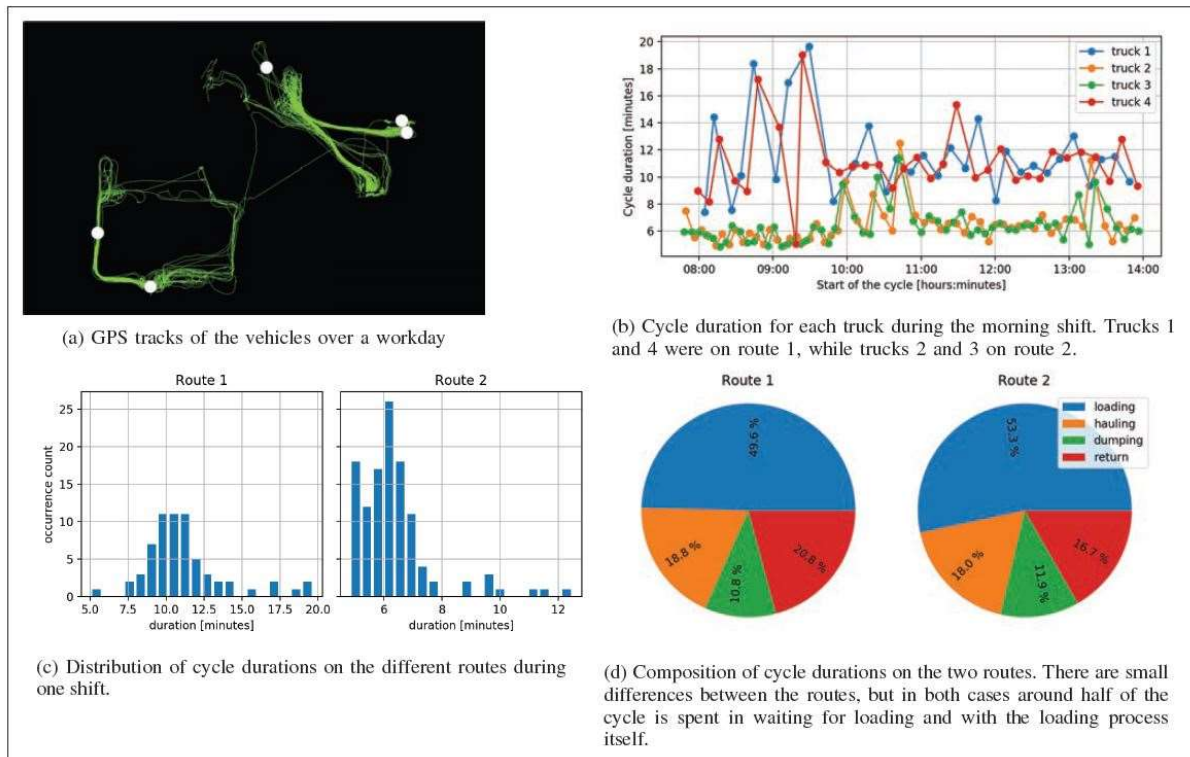


Figure 40 Data collection and analysis of construction site tests (Bucchiarone et al., 2020, p. 44)

Project managers can gain valuable insights into the running processes by viewing the views in the previous figure. It is intuitively possible to recognize and analyze deviations from the norm (e.g., heavier vibrations on the way, deteriorated road quality) on the fly (e.g. when hauling periods start taking longer on the same route as usual). Project managers can initiate appropriate adjustments and adaptations based on easily accessible, comprehensible, and current information (e.g., using more vehicles and improving service roads). (Bucchiarone et al., 2020, p. 44)

4.5.1.5 Challenges

The first challenge in this case study was that project managers and workers are usually pragmatic and practical professionals, although they may be curious and open-minded about the possibilities of using new technologies. It was reported that the construction industry has difficulty adapting and accepting new technologies. If they are to invest their time and money in a system, it must provide benefits for their work immediately. There is no doubt that long-term advantages are significant, but subjective priorities are shifting under pressure when competition for limited resources is fierce. (Bucchiarone et al., 2020, p. 44)

The other challenge brought up during conversations was the security issue. Despite the large size of construction sites, it is not possible to protect them at all times. Distributed resources of some value, such as gateway nodes, must be protected against theft in some way. (Bucchiarone et al., 2020, p. 44)

4.5.1.6 Conclusion

Case study five explained the use of the Internet of Things in construction based on using sensors (smart nodes) attached to the equipment working on site. As shown in Figure 40, it was possible to track the routes of the vehicles and hence estimate the consumed durations per each cycle. Such data was valuable for project management where for example, it indicated that half of the time was spent in the loading process, and hence project managers can act in accordance if they plan to finish earlier and think of a recovery plan if they go behind schedule. Such real-time data is a crucial solution to most of the challenges in construction management, where decision-makers can build their decisions on a concrete basis and then monitor the efficiency and consequences of the decisions. The challenges mentioned align with those mentioned in Chapter 3, which explains the lack of trust in new technologies and the risk of safety for the existing tools to gather data.

4.6 Case Studies Summary

Throughout the previously illustrated five case studies, different technologies of AI were utilized to provide potential solutions to save efforts, time, and money. A summary of these case studies is introduced as follows in Table 6:

CS Nr	Construction aspect	AI Technology	Purpose	Results
CS1	Public project cost forecasting	<ul style="list-style-type: none"> - Artificial Neural Networks (ANN) - ML (Supervised Learning) 	Estimate projects costs	<ul style="list-style-type: none"> - Projects' final costs were estimated with around 91% accuracy
CS2	Projects safety analysis	<ul style="list-style-type: none"> - Computer Vision - Deep Learning - AMRs 	Detect potential risks	<ul style="list-style-type: none"> - Danger potential was identified between the two machines successfully
CS3	Reports Analysis	Natural Language Processing	Analyse different causes of construction site accidents according to the OSHA database.	<ul style="list-style-type: none"> - Eleven causes of accidents were identified with occurring percentages by analysing over 16,000 accident reports.
CS4	Construction Management (Monitoring and Controlling)	Robotics (UAVs – Drones)	Monitoring construction site progress in cooperation with BIM	<ul style="list-style-type: none"> - A volumetric comparison was successfully made with an error of .012 M - Progress update was performed and reflected on project's time schedule
CS5	Construction Management (Equipment Performance Analysis)	Internet of Things (IoT)	Infrastructure Equipment performance, coordination and productivity were analysed.	<ul style="list-style-type: none"> - A platform was introduced where construction equipment was monitored, their performance was analysed, and GPS was used to coordinate their work.

Table 6 Case Studies Summary

5. Conclusion

This research indicates that Artificial Intelligence is emerging in the construction industry. Various technologies were researched to prove their functionalities and advantages in practice life. This research succeeded in achieving the four designed goals. The first goal of this research was to form a literature review about Artificial Intelligence, where six main branches of AI were discussed in detail in a friendly methodology to non-AI background readers. One branch was left behind, which was optimisation, due to its complexity and broad scope; while it is a popular topic, studying other branches that still need more investigation was more beneficial. The explanation of AI branches exceeded the theory part and gave practical examples from industries other than the construction industry.

The second goal of this research was to study the intersection between AI and construction activities. This goal was achieved by listing possible applications of each AI technology and tool in the construction industry. The main challenges of implementing AI in construction were cultural acceptance, data security, lack of talent, expensive initial investment, powerful computers and reliable internet access, big data handling, negative social impact and safety. The mentioned challenges, along with the applications of AI in construction, give a complete picture of the interactions.

Furthermore, the current use of AI in the construction industry was proven through five different case studies (Table 6) with diverse technologies, tools and purposes. Case studies involved Artificial Neural Networks (ANN) using a supervised learning classification of Machine Learning (ML), Computer Vision (CV), Deep Learning (DL), Natural Language Processing (NLP), Robotics represented in Unmanned Aerial Vehicles (UAVs) and (AMRs) and the Internet of Things (IoT). Those technologies delivered many purposes, including project cost estimation, site risk analysis, reports analysis, construction project monitoring and equipment performance analysis. This diversity demonstrated the validity of this thesis argument of the involvement of AI in many aspects of the construction industry.

The fourth goal of this research dealt with the future of AI in construction, which is handled within the following two sections.

5.1 Discussion

Studying the involvement of AI in construction against the challenges that are slowing down the progress of development gives a concrete picture of the current situation in the market. Although AI technologies are complex and hard to understand without proper studies, the five case studies were simplified as much as possible so that readers with non-AI backgrounds can understand the technology, its components, and how it performs from the very beginning of the idea to the possible results.

In Case Study 1, where ANN was used for forecasting the final costs of public projects, it was challenging to illustrate the technological components. One example can be the theory of how backpropagation works to minimize the error of weights included to find a constant weight value for each variable. The researchers in CS1 proved that the model could be used to forecast the final cost of construction projects, but it was not mentioned how they could earn the trust of government officials to build their estimation of construction project budgets based on a model on which they cannot see how it works, which is the drawback of the black box nature of Machine Learning in general. There is another risk concerning the confidentiality of the information obtained by the proposed model where construction companies might access it and hence determine their bid based on the lowest expected value. On the other hand, if the officials considered the values of the model while planning project budgets, it can incredibly minimize the risk of the incompleteness of projects due to financial reasons.

In Case Study 2, computer vision (CV) was combined with Deep Learning (DL) to eliminate the risk of autonomous excavator collision at construction sites. As explained in Chapter 2, computer vision technology provides the computer with eyes to see; in that case, DL was the processing mind of the obtained data from visuals. The study was successful since it already managed to verify the detection of danger when an excavator was about to hit another piece of equipment. It also included the Autonomous Excavator System, which falls under AI Robotics. This case study supports the argument for remote monitoring, controlling, and operating at construction sites, which, if combined with the Internet of Things technology, can lead the way to the safe application of autonomous equipment in construction sites. So, in short, the second case study combined three different technologies or tools: DL, CV

and AMRs, where they worked harmoniously to achieve a specific purpose. Despite the fact that operating equipment on sites is possible without human interference, there is still the risk of cyber attacks, as stated as a challenge in Chapter 3. Even if the autonomous proposal is proven valid, cyber attack risk will require human supervision so that supervisors can act at any time if the equipment behaves suspiciously.

The construction industry is full of data in many forms; as discussed in Case Study 3, Natural Language Processing helped identify eleven causes of accidents in construction sites. NLP in CS3 proved the ability to read over sixteen thousand accident reports and provide an analysis. NLP provides an excellent solution for handling Big Data in the construction industry. The future extension of this application will allow for generating automated reports, reducing the time consumed in reading and analysing reports. The error factor in reporting is expected to be reduced due to the minimised human interference in the report generation process. If a different look is given at Case Study 5, adding the IoT technology in collecting data from construction sites, the total error of the data collecting and reporting is minimised, forming a solid ground for decision-making and progress updates. For example, the smart construction platform, as in CS5, can give a better real-time understanding of the project performance and status. Despite the proven advantages, challenges were spotted in Case Study 5, represented in the resistance to change by the stakeholders involved in the study, where the introduction of new methods must convince the stakeholders of their feasibility. Furthermore, there was the fear of valuable smart nodes being stolen due to being attached in an exposed way, as shown in Figure 39.

In Case Study 4, only one type of robotics was discussed, while this branch of AI is full of solutions to explore, as shown in Chapter 3. Unmanned Aerial vehicles (UAVs), also known as drones, were integrated with BIM, which is already used in the construction industry. This integration can show that existing tools and technologies, such as BIM, can adapt to the newly implemented technologies in the industry. Moreover, this means that in the future, there could be the possibility to find all the technologies applied through digital twins for operation or monitoring construction projects or buildings.

5.2 Recommendations

Introducing Artificial intelligence to the construction industry is similar to the first introduction of computer-aided design (CAD) and Building information modelling (BIM). At the beginning of each, there were many challenges and no one expected to be part of the reality. However, CAD and BIM are part of the industry today, and they transformed the shape of the industry. BIM is considered a hot new topic in some parts of the world, while in others, it is part of the daily industry routine. Some jobs were no longer required; for example, the draftsman who used to draw drawings with pencils lost his/her job, and instead, they developed their skills to use Autodesk AutoCAD software, for instance. The conclusion is that AI, like other, introduced new technologies throughout construction history, is coming and will also be part of the daily professional routine in the upcoming years. A race started in the industry, and the faster stakeholders realise that the more they stay in the lead. It also depends on the capabilities of a country's infrastructure since IoT, for example, requires a 5th-generation network (5G) to perform efficiently.

After exploring this exciting topic, it was found that construction stakeholders must start dealing with the mentioned challenges to work on the main three construction pillars, safety, economics and functionality.

The first challenge is the lack of talent. It is recommended that construction stakeholders and research entities invest in attracting more talents from AI backgrounds to study the construction industry to generate ideas and innovations custom-tailored to fit the nature of the industry. The other way is to invest in talented construction professionals to learn more about AI tools and technologies so they can merge both in their tasks. A combination of construction professionals and AI specialists can also work, where transferable knowledge can be a valuable asset for construction entities. All three approaches can provide more solutions to the companies and reduce costs of purchasing technologies or software where they can rely on their development departments and avoid getting out of the market due to outdated or buying ready-made technologies.

This goal might be on a strategic level, where people in that position need to understand and learn more about AI, which makes proceeding in such developing

solution harder unless stakeholders at tactical and operational levels (most probably will younger generations) start to indicate the advantages.

The second spotted challenge was the cultural acceptance of adopting AI technologies, a global challenge in all industries. In that case, cultural acceptance includes building the trust to use technologies and extending it to the involved white and blue collars. For the white collars, one solution would be the Explainable AI (XAI) which mitigates the complexity and the black-box nature risk of AI Algorithms. Construction professionals must understand how the algorithms work and the basis of the proposed results or outputs. Using XAI will answer construction stakeholders' questions. On the other hand, blue collars will show resistance to adopting new interventions where they will fear losing their jobs. In this case, applying AI technologies and tools to the construction industry will require generating new jobs for the blue collars, and this can be one root of successful AI tools' implementation.

It is expected that the norms of the construction society will change in both negative and positive ways. Communication between professionals would be reduced due to the automated processes driven by AI. It can minimise the errors of human interference in the reporting systems, as illustrated earlier, but the interaction and the homogeneously between stakeholders would be reduced. Management style will be the key player to keep all the stakeholders involved, while this can be a proper introduction to the Agile mindset, for example. Agile is specially mentioned in this context since it was born in software industries. Involving more software with the proposed automatization can make construction a proper environment for adopting Agility.

In addition, Lean management practices will start gaining more popularity since it is a system that aims to eliminate managerial waste. Using AI can be expected to eliminate different types of waste in the construction industry, such as waiting time, which was evident in Case Study 5 (see Figure 40 - d); that waiting time was clearly shown as a big issue. Through IoT, it was quickly identified, and corrective action could be able to eliminate it. Also, in CS5, motion was monitored (see Figure 40 – a) and hence could be controlled, which is another type of waste according to Lean considerations. In addition to eliminating managerial waste, the use of the Last Planner System, which is an implementation process of Lean Management, on the one hand, can help to bring all the stakeholders together, while on the other hand can

take advantage of the accurate reporting and monitoring systems provided by AI to enhance the decisions for the future.

Furthermore, the construction industry suffers from massive data produced in the lifecycle. AI (by its nature) produces massive amounts of data, known as (Big Data), which can be solved using AI tools, but optimisation and sustainability of data usage will remain a question that needs further specialists to shape the new form of the working environment.

One more critical viewpoint, it is expected that small-scale construction entities will have to find a way to survive since adopting technologies is expensive, and even though AI adoption is known to be slow, it is happening and has proven beneficial.

It has always been the question of if AI will replace human beings, and a very straightforward answer from the author's perspective is that AI cannot replace humans; AI will change the way to think and act as an assisting tool. The nature of many jobs and the work environment will change, and learning from history lessons, people and industries will adapt.

The future of AI in construction is another exciting topic that can be discussed further in the following section.

5.3 Future Research

The presented research can be used as a starting point for future exploration of AI in construction. This research was formed of detailed analysis of AI elements and their possible use in the industry, which presents a potential for further narrowed-down studies and frameworks dealing with specific technologies in the construction industry. Future researchers can take advantage of the use cases mentioned in this research from other industries, where they can generate publications to transfer the experience and lessons learned from those industries. Hence they can be able to mitigate the unseen risk of implementing the technologies from scratch.

Further literature studies can investigate the current involvement of Knowledge-Based systems and Optimisation since they were not included in this research due to the broad scope of AI technologies that one research could not cover in detail. Nevertheless, Optimisation is well investigated in other publications, while it is recommended to investigate the Knowledge-Based Systems' uses in construction as there is less focus on them.

Future research can focus on each AI technology and study how it can be implemented in real life, including the success factors. Success factors can be, for example, the required preparations for adopting the specific technology in a construction environment, such as stakeholder training, hardware compatibility, innovative software, and data security. Furthermore, future research can study how to build trust in the provided solutions using AI, where cultural acceptance is one major factor in applying AI in construction.

Furthermore, the sustainable use of big data in construction can be an exciting research area since most AI technologies can produce vast amounts of data, which is already a challenge for construction stakeholders. The initial costs of using AI technologies is another challenge, where a study can analyse the relationship between the costs of using AI in construction and the influence on the profit, duration and resources of the project.

Future research can also study how different technologies and tools can work together to achieve different purposes and workflow harmony. From a legal aspect, implementing AI in the construction industry needs further investigation and study, where the legislation must cope with the recent developments and govern the

relationship between stakeholders. In addition, there is a lack of research on the ethics and morals of using AI in construction, which would shape the culture of using these said technologies.

Involving more AI tools and technologies is challenging since it relies on how much construction stakeholders know and understand them and their possible uses to add value to their running business. A study can investigate how AI can be affordable in the construction industry for small-scale firms and present a simplified framework for such an approach. It was also noticed that current construction industry trends are not well investigated to include the use of AI. From a managerial perspective, construction researchers and entities can start working on how Lean management and Agile mindset benefit from AI. Researchers have much potential to work on increasing project profitability, giving better quality control, eliminating managerial waste, and providing real-time visual monitoring and decision-making.

Declaration of Authorship

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This declaration should be handed in to the chairperson of the examination board upon submission of the Master's thesis.

Master's Thesis Declaration

I hereby declare that the attached Master's thesis was completed independently and without the prohibited assistance of third parties, and that no sources or assistance were used other than those listed. All passages whose content or wording originates from another publication have been marked as such. Neither this thesis nor any variant of it has previously been submitted to an examining authority or published.

07.07.2023

Date

A handwritten signature in black ink, which appears to read 'Mohanad Ali', is written over a horizontal line. Below the line, the text 'Signature of the student' is printed.

Signature of the student

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