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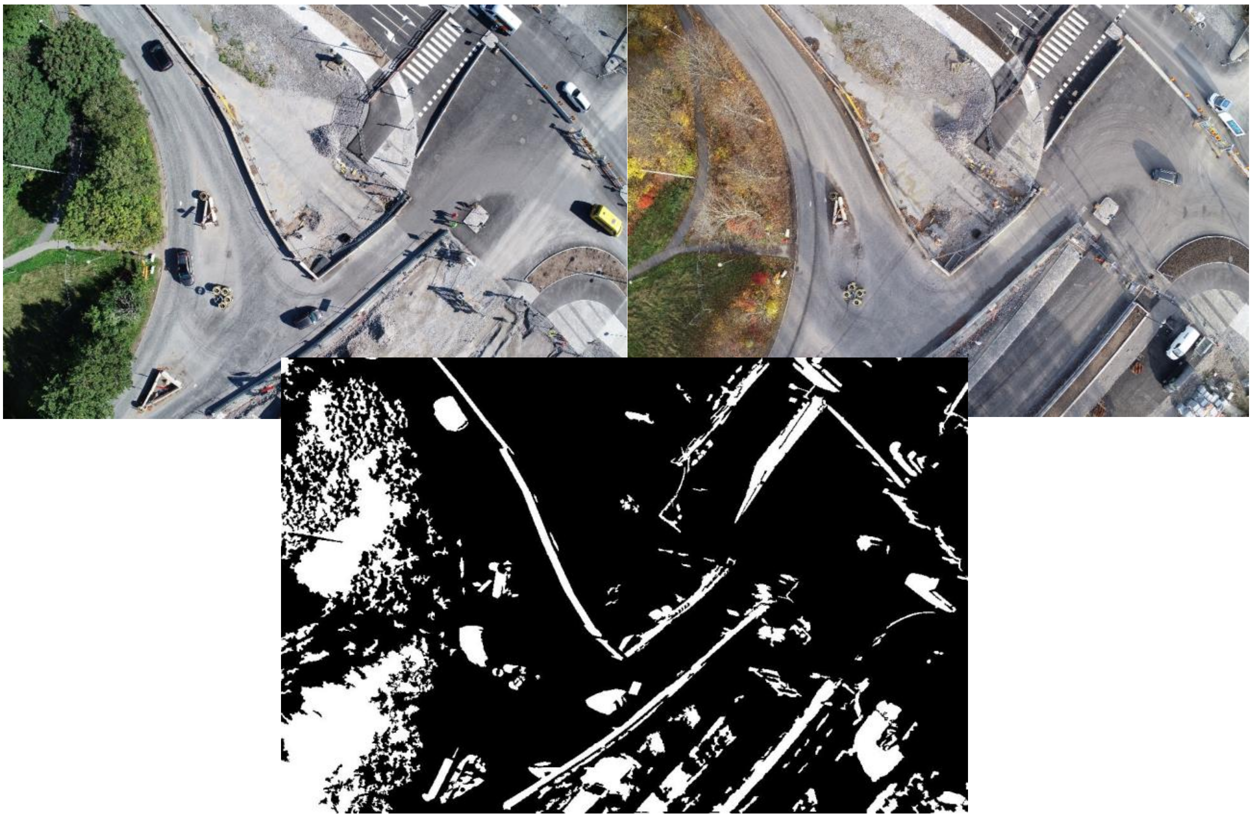

Change detection in drone-captured image data for the construction sector

Exploring the possibilities and obstacles of implementing automatic progress monitoring in a dynamic industry

Master’s thesis in Design and construction project management

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CHALMERS UNIVERSITY OF TECHNOLOGY

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MASTER’S THESIS ACEX30

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Cover:
Two images of an infrastructure project taken at two different times along with an image showing detected changes in white and no changes in black.
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ABSTRACT

Low productivity, expected labour shortages and hazardous work environment are some of the construction sector's problems. Digitalisation has revolutionised many other industries, and the construction industry is starting to realise the possibilities this technology can have to meet the industry's challenges. However, the fragmented and project-based construction industry and the dynamic project processes, that characterise construction projects, present many obstacles to effective progress monitoring. Today's monitoring progress is primarily manual, subjective, and irregular. This, in turn, leads to late changes, errors and delays, and often cause construction projects to fail to meet deadlines and budgets. Using change detection algorithms to identify changes that have happened over time in drone-captured images could facilitate the work on site by, for example, quickly identify areas of interest, give early warnings of deviations from the design documents, and highlight safety concerns. Therefore, the aim with this master thesis is to investigate how AI can be utilised to automatically monitor construction project progress from drone-captured data. Also, the characteristics of the industry that can affect the use of such a system are studied. The method of this thesis consisted of a literature review, pre-study interviews, a study visit and code testing. The results indicate that changes can be detected using AI on drone-captured data. However, adjustments or improvements need to be made for this to be truly useful. The results show multiple areas where this type of process needs to be adjusted to improve accuracy and make sure this method fits automatic progress monitoring of the dynamic construction industry. There exists, a lack of datasets and national model libraries on construction objects and images, as well as a lack of advanced digital knowledge and competences in the workforce. Nevertheless, change detection in images captured by drones could be used to address challenges such as safety, productivity and labour shortages. However, this will require a rigorous routine that describes how to collect, analyse, store and handle the data as well as frequency.

Key words: Artificial Intelligence, Change detection, Construction industry, Drones, Progress monitoring.

Förändringsdetektering i drönarfångad bilddata för byggsektorn.

Utforska möjligheter och hinder med att implementera automatisk framdriftsövervakning i en dynamisk bransch.

Examensarbete inom mastersprogrammet Design & Construction Project Management

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SAMMANFATTNING

Låg produktivitet, förväntad brist på arbetskraft och farlig arbetsmiljö är några av problemen som finns i byggsektorn. Digitalisering har revolutionerat många andra branscher och byggbranschen börjar inse möjligheterna denna teknik kan ha för att möta branschens utmaningar. Den fragmenterade och projektbaserade byggbranschen och de dynamiska projektprocesser som kännetecknar byggprojekt utgör dock många hinder för en effektiv framdriftsövervakning. Dagens övervakning av framdrift och förändringar är ofta manuell, subjektiv och oregelbunden. Detta leder i sin tur till sena förändringar, fel och förseningar och orsakar ofta att byggprojekt misslyckas med att hålla tidsfrister och budgetar. Att använda förändringsdetekteringsalgoritmer för att identifiera förändringar som har skett över tid i drönarfångade bilder skulle kunna underlätta arbetet på byggarbetsplatsen genom att, till exempel, snabbt identifiera områden av intresse, ge tidiga varningar om avvikelser från projekteringsdokumenten och lyfta fram säkerhetsaspekter. Därför är syftet med denna masteruppsats att undersöka hur AI kan användas för att automatiskt bevaka byggprojektets framdrift utifrån drönarfångad data. Dessutom studeras de egenskaper i branschen som kan påverka användningen av ett sådant system. Metoden i denna uppsats bestod av en litteraturundersökning, förstudieintervjuer, ett studiebesök och testning av koder. Resultaten indikerar att förändringar kan upptäckas med användning av AI i drönarfångad data. Justeringar eller förbättringar måste dock göras för att detta verkligen ska vara användbart. Resultaten visar flera områden där denna typ av process behöver justeras för att förbättra noggrannheten och för att säkerställa att denna metod passar automatisk framdriftövervakning av den dynamiska byggbranschen. Det finns brist på datamängder och nationella modellbibliotek på byggobjekt och bilder, samt brist på avancerad digital kunskap och kompetens hos tjänstemän och yrkesarbetare. Trots detta kan förändringsdetektering i bilder tagna med drönare användas för att hantera utmaningar som säkerhet, produktivitet och den brist på arbetskraft som byggbranschen står inför. Detta kommer dock att kräva en rigorös rutin som beskriver hur man samlar in, analyserar, lagrar och hanterar data samt beslut om hur ofta detta ska göras.

Nyckelord: Artificiell intelligens, Förändringsdetektering, Byggindustri, Drönare, Framdriftövervakning.

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Preface

The following thesis is a degree project of 30 higher education credits, which was carried out as a final step of the master’s Design and construction project management at the Department of Architecture and Civil Engineering, Chalmers University of Technology. We are proud to have written a master's thesis on an important and interesting subject that is very relevant in the construction sector. Valuable knowledge has been gained throughout this thesis and it has been an enjoyable process to write it.

The work was conducted during the spring semester of 2022 in collaboration with NCC Sverige AB. We would like to extend a special thank you to our supervisor from NCC and Chalmers, *Christina Claeson-Jonsson*, who with great commitment has contributed with knowledge, expertise on the topic, and guidance throughout the degree project. We would also like to thank *Andreas Fransman* and *Niklas Bruske* at NCC who have been of great support for exchanging ideas during the thesis. Furthermore, we would like to thank our opponents *Maryam Kiani Hashemiesfahani* and *Madeleine Skogh* for their feedback over the course of this thesis. Finally, we would also like to thank everyone who participated at the study visit, who contributed with their knowledge in our interviews, and everyone else who have been involved in our master thesis in some way.

Göteborg 8 June 2022

Elaf Ahmad
Marion Lissmatz van de Laak

Notations

AI – Artificial intelligence

AR – Augmented reality

BIM – Building Information Modelling

CNN – Convolutional neural network

CWNN – Convolutional Wavelet Neural Network

GAN – Generative adversarial networks

GCS – Ground Control Station

GDP – Gross Domestic Product

GDPR – General Data Protection Regulation

GPS – Global Positioning System

IOT – Internet of things

ML – Machine learning

MR – Mixed Reality

PCA – Principal component analysis

RNN – Recurrent neural networks

RPV – Remotely Piloted Vehicles

SAR – Synthetic Aperture Radar

UAS – Unmanned Aerial System

UAV – Unmanned Aerial Vehicles

VR – Virtual reality

VTOL – Vertical take-off and landing

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1 Introduction

The following sections are intended to provide the reader with a clear understanding of the study's background, projects aim, research question, and project limitations. Here will also be a presentation of the thesis outline explaining the structure of the rest of the thesis.

1.1 Background

The construction industry represents a large part of a country's GDP (European Construction Sector Observatory, 2021; Navon, 2005; Nikmehr et al., 2021; Ribeirinho et al., 2020) and it is also an industry associated with low productivity (Westlund et al., 2014), safety issues (Arbetsmiljöverket, 2022), resources wastage and a large environmental impact (European Construction Sector Observatory, 2021; Schönbeck et al., 2020; Westlund et al., 2014). This means that the construction industry is of huge importance for society, the economy and the environment (European Construction Sector Observatory, 2021) and there is an urgent need to tackle its issues. Digitalisation has been foreseen to have a positive impact in many of the issues the construction industry faces (Bosch-Sijtsema et al., 2021; Nikmehr et al., 2021), however, the technical development in construction faces a conservative and slow industry where the digital solutions are far behind other industries (Agarwal et al., 2016; Ribeirinho et al., 2020). It has also been shown that this industry has a low familiarity with research and development regarding technological solutions (García de Soto et al., 2019).

For construction management, it is important to have control over progress and safety aspects. Despite this, the construction industry has fallen behind other more industrialised sectors such as manufacturing, retail, education and finance (Borowska, 2020; European Construction Sector Observatory, 2021; Samuelson, 2021). Today most control processes are done manually which are tedious and error prone activities occupying much time of workers and management (Alizadehsalehi & Yitmen, 2019; Puri & Turkan, 2020). Other industries have successfully implemented the use of artificial intelligence and automation in their processes and achieved increased productivity as well as reduced cost and environmental impact (European Construction Sector Observatory, 2021; Samuelson, 2021). It is important for construction to look at these good examples and learn from them (Bosch-Sijtsema et al., 2021).

When it comes to digitalisation, the concept of Building Information Modelling (BIM) has started to impact projects in the industry, but this also means that other technologies are overshadowed in favour of BIM making it even harder to implement other technical solutions (Schönbeck et al., 2020). For example, Artificial Intelligence (AI), that other industries use to great effect, are not nearly as present in the construction industry (Abioye et al., 2021). Drones, or Unmanned Aerial Vehicles (UAVs), are also used in many different industries to a range of application (Greenwood et al., 2019). It has been shown that they can effectively perform mundane, time-consuming and dangerous tasks and be efficient and accurate in capturing near real-time data (European Construction Sector Observatory, 2021; Jeziorska, 2019; Said et al., 2021). A lot of data is collected on construction sites not only by drones but also by cameras, sensors, and other robots (Agarwal et al., 2016). This information is then often manually handled by people which takes a lot of time and does not create an accurate representation of the site

(Mahami et al., 2019). However, this data has the potential to be automatically analysed using AI and machine learning, something that industries such as agriculture, energy, remote sensing and mining are doing (Goudarzi et al., 2019; Higuchi & Babasaki, 2017; Rogan & Chen, 2004; Said et al., 2021). This could mean automatically detecting changes and following the project process almost in real time to identify problems and deviations from time-plans and project plan also in construction (Calo et al., 2017; Mahami et al., 2019).

From the research conducted in this thesis, three steps of a progress monitoring process were identified: (1) Change detection, (2) Change identification and (3) Change notification. This thesis will, however, only look at the first step including the challenges the construction industry face, the state-of-the-art of digitalisation in the construction industry and the potential benefits of applying this technology from other industries.

1.2 Project aim

This thesis will look at how digital tools such as drones and artificial intelligence can help address the challenges the construction industry faces. To investigate the possibilities of detecting changes in drone captured data and how this would affect construction work. Furthermore, to understand existing technologies and their application to the construction industry and explore the benefits these methods can create. The research will primarily be done from the perspective of a large Swedish contractor that works widely in the Nordic region. This contractor has been using drones from 2017 and are now starting to work with automatic detection. Hence, the aim of this research is therefor to do an explorative study on what possibilities there are with using AI and change detection in progress monitoring for the construction sector and which obstacles that the industry might face in implementing this technology.

1.3 Research questions

This section presents the research questions that are to be answered in this master thesis and will help achieve the aim and have been formulated as:

- RQ1: How can change detection in drone-captured data be utilised on the construction site?
- RQ2: What characteristics of the construction industry can affect an implementation and use of change detection in drone-captured data?

1.4 Contribution

As of now, there are few studies on change detection and AI in drone-captured data in the construction industry. Those studies that do exist mainly focus on single cases or not on all these aspects together. For example, there are a few more studies on AI and drones, change detection and drones, drones and construction, and AI and construction but not on the combination of all these areas.

This means that this thesis could work as a starting point for further research on this area that hopefully helps the industry to take the first steps towards automating their progress monitoring processes. The hope is that this study can identify areas that could be of interest for what to consider when trying this technology and creating working processes that the industry would benefit from. Another contribution is to give perspectives on what other industries are doing and potentials for transferring that knowledge into the construction sector.

1.5 Delimitations

This thesis will focus on the managerial parts of digitalisation that stretches further than understanding the basics of the technology. It will look at different methods of analysis but not go into detail how those methods are built or how they work. It will not look at other ways to address current challenges but addresses them from the perspective of digitalisation and specifically progress monitoring in relation to drones and artificial intelligence. The aim is not to invent, create or discover a new way to measure progress digitally but to look at existing models and investigate how those could affect the industry. Thereby, there will be no analysis of the models used and their quality. Neither will the thesis develop or create new ideas to solve problems the construction industry faces but explore solutions other industries have implemented for similar issues. The thesis will not go into detail on numbers regarding positive impact, for example productivity and time saving but rather establish whether or not there exist a possibility for improvement.

The literature review will include different carriers of the technology capturing data, such as Satellites and ground-based vehicles, but the thesis will then apply this knowledge to the use of drones which may affect the accuracy of the result. Furthermore, the report will only investigate the possibility to detect superficial changes from one contractor and one type of drone camera. Another delimitation is that the thesis will only look at identifying that a change has happened and not what and where that change is. Neither, has this study calculated or identified any measurable results in accuracy of detection or benefits of implementation of this method. This master thesis is concerned only with the construction stage and the tests have been done on images only from infrastructure projects, however, it is assumed that the results can be applied to building projects as well. This thesis will look at applications suited to rotor drones but take information and knowledge from other types of drones and satellites, and planes as well. The literature used will be from all over the world, but the images tested, and the data collected will come from Sweden and the result will be applied to the Swedish construction industry. However, the results may be applicable in other countries as well.

1.6 Thesis outline

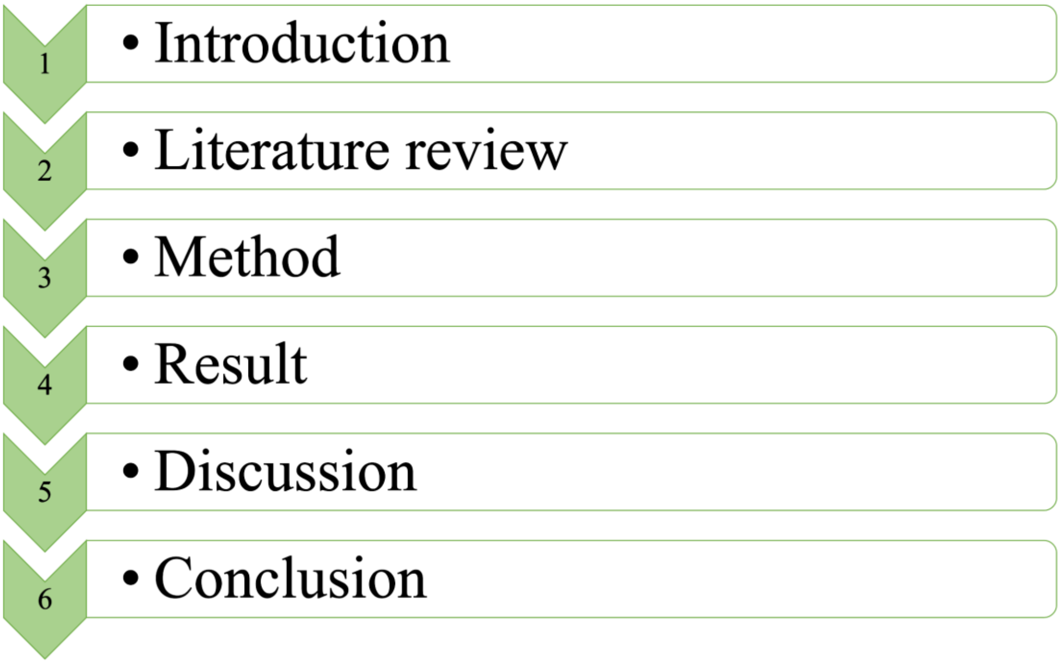


Figure 1: Flowchart of the thesis outline from introduction to conclusion.

Figure 1 describes the outline of this master thesis. It starts with the introduction that presents background and aim of the thesis together with research questions, delimitations, and contributions. Chapter 2 then addresses the existing research on the area of automatic change detection in construction and other industries. This to identify a gap in the research and create a base for further discussion. Chapter 3 presents the procedure that this study has followed. It includes description of the approach for the literature review, pre-study interviews, study visit and testing of codes. Chapter 4 presents the results from the pre-study interviews, study visit and testing of the codes. Chapter 5 discuss and analyse the literature and results and finally, in chapter 6 the research questions are answered, and further research recommendations are presented.

2 Literature review

The theoretical framework will look at the existing literature on digitalisation of construction with focus on digitising progress monitoring. This will start with identification of challenges in the industry followed by a state-of-the-art analysis of digitalisation in construction today. This will then be followed by a look into drones, artificial intelligence and change detection. How these technologies work and how they are used in construction but also in other industries. Finally, a review of the laws, ethics and sustainability aspects of change detection in drones are presented.

2.1 Challenges in the construction sector

The construction industry has underperformed for some time now and, by being the biggest industry in the world, that has a large effect on society (Ribeirinho et al., 2020). It is estimated that in order to meet the needs the world faces the industry has to build infrastructure to a cost of over 50$ trillion to keep up with the global growth of GDP. This will require new ways of working in the construction industry and put high requirements on increasing productivity and efficiency (Agarwal et al., 2016). Furthermore, there is a demand for a reduction in environmental impact from the construction industry which also require new, more efficient, ways of working (Agarwal et al., 2016; Nikmehr et al., 2021). Technology can address many of the problems the industry faces today but implementing digital solutions are hard and it also create new types of challenges (Bosch-Sijtsema et al., 2021; Nikmehr et al., 2021). The construction industry is now facing digitalisation, globalisation and industrialisation all at the same time, something other industries has adapted to over time. This creates challenging but rewarding conditions for the entire industry (Ribeirinho et al., 2020).

2.1.1 Fragmented and project-based industry

The construction industry is a project-based industry with one-off, often unique, production and with temporary project organisations. It can be said that projects are engineer-to-order and that this means that the industry is a production system which, for construction also includes design (Vrijhoef & Koskela, 2005). It is a fragmented and complex industry with many companies where projects have multiple specialised stakeholders and actors of different sizes in their value chains(European Construction Sector Observatory, 2021; Q. et al., 2015). This fragmentation makes it hard to keep productivity and efficiency up and make innovation and digitalisation difficult and slow (European Construction Sector Observatory, 2021; García de Soto et al., 2019). It makes collaboration very difficult and as many of the stakeholders involved are smaller companies it makes it hard to make large investments in improvements because of their low economies of scale. The fragmentation and low collaboration also contribute to friction as companies tend to do a lot of risk aversion (European Construction Sector Observatory, 2021). Accountability is often spread out over many actors and so is the responsibility for development and innovation (European Construction Sector Observatory, 2021; Ribeirinho et al., 2020). The complex structures that today's companies are expected to build require a lot of coordination between companies and make projects hard to repeat which are two main reasons to the industry's low level of productivity (Ribeirinho et al., 2020).

2.1.2 Productivity issues, cost and time overruns

The challenges that the construction industry faces today mostly have to do with a low degree of digitalisation. This in turn leads to poor productivity and a slow development (Novak et al., 2018). While other industries have had an increase in productivity of approximately 2.8 % per year, construction has only had an increase of around 1 % per year (European Construction Sector Observatory, 2021) and in some areas of the industry the productivity has even decreased between now and 1990 (Agarwal et al., 2016; Wingtra, n.d.). Compared to manufacturing the difference in increase is even bigger as they had an increase in productivity of 3.6% per year compared to construction's 1% (European Construction Sector Observatory, 2021). Construction has fallen behind general economic productivity growth and over the last 20 years the increase in productivity for construction has only been a third of economic averages (Agarwal et al., 2016; Ribeirinho et al., 2020).

The low productivity and resource wastage that the industry is characterised by contribute to that large construction projects often have time overruns for up to 20 % (Agarwal et al., 2016; Wingtra, n.d.). This is more a rule than an exception (Agarwal et al., 2016) as over 90 % of projects are either delayed, over budget or lack proper planning (Schober, 2020). Rather than actually plan for the time and money a project would require, companies tend to earn back through error correction instead. The construction industry also stands before a decrease in profitability margins (European Construction Sector Observatory, 2021). Profitability is already lower than most other sectors of the economy (Nikmehr et al., 2021), especially for contractors, and the lack of productivity development will increase the gap (European Construction Sector Observatory, 2021). Construction industry is especially sensitive to changes in economic cycles (Ribeirinho et al., 2020) and the already narrow margins increases the risk for the industry to break apart if they fail to develop (European Construction Sector Observatory, 2021).

2.1.3 Environment and safety

The construction industry is a very large contributor of greenhouse emissions and waste as well as being a large energy consumer (Nikmehr et al., 2021). The construction industry in Sweden contributes to as much carbon emissions as all Swedish cars combined and the production stage emit just as much emissions as 50 years of facility management. It is, therefore, necessary to work to decrease the emission from the production of buildings and infrastructure (Westlund et al., 2014). For example, does 8 % of global emissions come from cement production (Ribeirinho et al., 2020). The construction industry also creates hundreds of millions of tons of waste per year only in the EU, making them the biggest waste creator in the union (European Construction Sector Observatory, 2021). There is also a need to reduce energy and water use, something technology could support (Ribeirinho et al., 2020).

The construction industry has more serious accidents than most other industries. The projects have many different actors, and the workplaces is often temporary creating a messy and dynamic work environment prone to accidents (Arbetsmiljöverket, 2022). Moving around the construction site can be dangerous and sometimes people must go to remote and hazardous locations to perform their work. They might also have to deal with repetitive tasks that can be tiring and dull (European Construction Sector Observatory, 2021). Consequently, the construction managers often go on safety inspection rounds together with the safety coordinators to make sure that everyone is safe when they are working. These routines are especially important in a risk full work environment and needs to be done frequently (Elghaish et al., 2021). For a long time, the construction sector has been known to be stressful and is ranked as the third most stressful industry according to Binti Abidin (2014). There are a lot of sources that contribute to stress, and one of them is the large amount of information that some employees deal with in their everyday work. Information overload, as it can be called, can cause danger to people in form of for example burnout, depression and overwork (Modijefsky, 2021).

2.1.4 Expected labour shortages

In the construction industry manual labour makes up a large part of the production. There is already a lack of skilled workers (European Construction Sector Observatory, 2021; Ribeirinho et al., 2020) and this is expected to increase as a large portion of today's construction workers are retiring or are planned to retire soon and there will not be enough workers to replace them (European Construction Sector Observatory, 2021; Nikmehr et al., 2021). In the USA around 41 % of the current workforce in construction is planned to retire by the year 2031 (Ribeirinho et al., 2020). One of the most important things to do in order to drive the market, according to the European Construction Sector Observatory (2021), is to look at technology to help with this labour shortage through higher productivity so that less workers are needed (European Construction Sector Observatory, 2021). New methods of construction are needed to fill the space in the work force that is created by leaving workers (Ribeirinho et al., 2020).

2.1.5 Dynamic project process

Most construction projects are dynamic all the way through the process with major changes taking place until the final steps of production (Borowska, 2020). A dynamic building process that is also fragmented are hard to keep control of (European Construction Sector Observatory, 2021; Ribeirinho et al., 2020). The construction industry's project-based nature and dynamic processes puts control function under a lot of pressure (Josephson & Larsson, 2001) and compared to other industries the construction industry has underdeveloped and slow systems for monitoring (Navon & Sacks, 2007). Many projects go over time and over budget often because there is too little knowledge about where in the process a project is (Josephson & Larsson, 2001). During a project, there are often also additional, unpredictable changes that are introduced in the construction process. These changes come from different stakeholders and for different reasons as well as at any stage in the construction process which may result in delays and increases in cost and resource demands (Q. et al., 2015). Additionally, the changes that occur naturally in the process of a construction project also need to be monitored and properly detected to reduce the losses that could come from failing to identify defects and interruptions of the project process in time (Alizadehsalehi & Yitmen, 2019; Josephson & Larsson, 2001; Q. et al., 2015). Both the pre-planned progress in a project and the additional changes added requires a robust system for detecting changes that happen in the physical production (Alizadehsalehi & Yitmen, 2021; Puri & Turkan, 2020). In order to keep an effective progress monitoring there is a need to systematically collect accurate and extensive data of the current, as-built, state and compare it to the plan, the so called as-planned model, or other earlier states. Construction delays can be avoided if enough data from the construction site is collected frequently and analysed in an effective way (Puri & Turkan, 2020).

Monitoring progress is a very complex undertaking because of the fragmented and complicated project-based industry (Alizadehsalehi & Yitmen, 2019) and most of it are today done manually (Mahami et al., 2019). Today, the project manager spends a lot of time on progress monitoring and therefore lack the time for decision making and working towards getting their project to reach its goals in time (Zaimi et al., 2006). Manual collection of data on the as-built state can also be subjective and there might be a need for additional site visits due to incomplete or faulty information (Puri & Turkan, 2020).

2.1.6 Low digitalisation level and unique needs

Digitalisation could be a solution to many challenges that the construction industry faces (Nikmehr et al., 2021) yet construction is far behind most other industries in technological development. There is a lack of investment in research and development in the industry (R&D) (Agarwal et al., 2016; Bosch-Sijtsema et al., 2021; Ribeirinho et al., 2020) and research show that construction is behind in implementing and adopting technologies (Bosch-Sijtsema et al., 2021) as well as there is a gap in research itself for exploration of technologies specific for construction (Schönbeck et al., 2020). There is also a lack of competence regarding digital tools and a need to retrain and educate the work force as well as attracting people with digital skills (Bosch-Sijtsema et al., 2021). Thus far the construction industry has had a hard time appealing to people with digital skills (Ribeirinho et al., 2020) and the construction industry has a specifically low level of digital competence already (Ribeirinho et al., 2020). European Construction Sector Observatory (2021) means that the lack of digital skills is one of the main challenges the construction industry faces and that it can stay in the way of implementing technologies such as artificial intelligence (AI), augmented and virtual reality (AR and VR) and systems with sensors and digital twins (European Construction Sector Observatory, 2021). It is also an industry with unique needs. The dynamic project process and fragmented value chains, along with site work and systems based on manual data collection, makes it hard to introduce technologies other industries have had success with (Bosch-Sijtsema et al., 2021; Navon & Sacks, 2007). Furthermore, there are specific technical challenges in the construction industry that slows down the development further (Agarwal et al., 2016).

2.2 State-of-the-art of digitalisation in construction

As mentioned, the level of digitalisation in the construction industry is low compared to most other industries (Ribeirinho et al., 2020; Samuelson, 2021). The advantages and possibilities with digitalisation are many and for most industries this is a known fact (Agarwal et al., 2016; Ribeirinho et al., 2020). Technologies such as Artificial Intelligence (AI), Building Information Model (BIM), Big data, digital twin and Internet of Things (IoT) has proven to increase efficiency, productivity, quality, precision, safety and security (Agarwal et al., 2016; European Construction Sector Observatory, 2021; Frank et al., 2019; Nikmehr et al., 2021; Perera et al., 2021). In the construction industry, however, the slow technological development has caused the values of digitalisation to remain a very unexplored area for a long time (Schönbeck et al., 2020). It is first now, in later years, that the need and value of new technologies seem to get more and more attention also in the construction industry (Samuelson, 2021). Although BIM is a large concept in the construction sector there are other technologies that also can improve the industry (Schönbeck et al., 2020), especially combined with drones. Those are AI, IoT and immersive technologies such as AR and VR (Elghaish et al., 2021; Schönbeck et al., 2020). However, despite potential with these other technologies, a lot of focus is put into BIM, which can cause other technologies to become underprioritized (European Construction Sector Observatory, 2021; Schönbeck et al., 2020).

2.2.1 The use of technology in construction today

Today, digitalisation in the construction industry, especially in the production process, still includes many manual tasks where the information is kept on paper and collected by hand. There is today very little investment in R&D and technologies with high initial costs are not used despite claimed benefits (Agarwal et al., 2016). The digitalisation level also varies from country to country. In the EU there is a substantial difference between countries in how far they have reached in technologic development for the construction industry. The use of BIM can be found a lot in the construction industry today. However, thus far, its use is limited mostly to larger projects, and it is mostly utilised in the design phase (European Construction Sector Observatory, 2021). This technology is seen as a backbone to digitalisation in the construction industry and a base for further digital development (Samuelson, 2021). Nonetheless, there are also views that too much focus on BIM can prevent other technologies from surfacing (Schönbeck et al., 2020). European Construction Sector Observatory (2021) means that data acquisition technologies, such as sensors, 3D scanning and IoT, are the place to start when digitising the construction industry. These technologies collect data that the technological system consists of making it possible for other technologies to make an impact. However, despite the appeared importance of these technologies their use varies a lot. Over later years it seems that the use of sensors and the interest of doing so has increased significantly. This has then led to an increase in the use of drones, also called Unmanned Aerial Vehicles (UAVs), to combine with these sensors. There is also a growing interest in AI technologies which could indicate that a development of those is coming (European Construction Sector Observatory, 2021). 3D printing and robotics is not yet common in construction except for the limited use of drones but there seems to be knowledge about some potential the technology could have (European Construction Sector Observatory, 2021; Samuelson, 2021) and there are predictions that these technologies are soon to reach wider use (Bosch-Sijtsema et al., 2021). The industry has begun to embrace drones for remote observations and monitoring to reduce the risk to people when they do not have to be in dangerous and hazardous situations (Nikmehr et al., 2021). Thus far, however, the research on drones in construction has been exploratory mostly looking at potential and the total research on the topic is limited. After 2016 the number of studies began to increase and first then drones in construction could be considered an area of research (Elghaish et al., 2021). There are many technologies that shows potential but there are very few of them that are applied in the industry to any larger extents (Bosch-Sijtsema et al., 2021; European Construction Sector Observatory, 2021).

2.2.2 Research on digitalisation and drones in construction

Even in research today there is a lack of focus on these technologies. In a study made by Schönbeck et al. (2020), where they looked at research on technologies and digitalisation in construction, especially automation and industrialisation. Management was a lot more common as a research topic and there were only a few studies that addressed both management and aspects of technology (Schönbeck et al., 2020). In a study made by Samuelson (2021) it was found that the most addressed technologies that are studied in the construction industry today is general technologies and BIM, as mentioned before. Technologies such as automation and robotics as well as AI and machine learning exist but are less prevalent. Despite this, the potential of these technologies is deemed to be high and there are many ideas on how AI could be used and benefit the industry (Samuelson, 2021). In a study ordered by the European Commission the European Construction Sector Observatory (2021) looked at digitalisation in the construction industry dividing digitalisation into three parts: *Data acquisition*, *automating processes*, and *digital information and analysis*. *Data acquisition* includes sensors and IoT as well as 3D scanning and covers the collection of data such as temperatures, geo-localisation, energy use and more. This is of vital importance in all phases of a construction project, from planning to facility management. *Automating processes* refers to technologies such as robotics, drones and 3D printing. These are tools important in the construction phase where they can help develop the building process by increasing quality and reduce labour work and safety issues. *Digital information and analysis* refer to BIM, AI, virtual reality (VR) and augmented reality (AR) as well as digital twins. This is the crucial part needed to handle the information created by and needed for the two previous categories. It can help create real-time flows of important information. Many of the technologies under these three categories are connected closely and, in many ways, they are needed to create a functioning system in all steps in the life cycle of a building. This study showed that working on one technology alone will not create a large development trend in the industry but there is a need to look at the whole eco system of technologies (European Construction Sector Observatory, 2021). Research also shows that there is a need to disrupt the current process and those who do will see a lot of profit and increase in productivity (Agarwal et al., 2016; Ribeirinho et al., 2020).

Regarding the lack of research for drones, Elghaish et al. (2021) summarised different studies made on drones in construction. One of them were using drones to create 3D maps of construction sites and buildings. This showed that with the use of drones it is possible to create a multi perspective view of a construction site creating a greater interaction through 3D models. Another study looked at drones as well as other ground-based robotics for monitoring processes such as surveying, progress monitoring, marketing, inventory, logistics, assessment of health and safety, and hazardous detection. A third study looked at monitoring of components in infrastructure. Elghaish et al. (2021) only found three papers specifically addressing drones in construction progress monitoring. One paper looked at drone-captured data for creating a panorama for helping identify site conditions and another looked at an automatic process of detecting road designs with layered surfaces. The third looked at using drones for a first-person view of a construction site for monitoring and communication. For papers focusing on inspection on the construction side the same authors found only a few papers, some about combining drones with BIM for inspection tasks creating fly paths and an automated system for triggering inspections. There is a large gap in the research, but drones are an area with lot of potential (Elghaish et al., 2021). When it comes to research on change detection in construction sector, there are few studies and little knowledge, and the studies that have been done are on single cases (European Construction Sector Observatory, 2021; Schönbeck et al., 2020).

2.2.3 Manual progress monitoring

As mentioned in earlier chapters, a lot of activities in the construction industry are done manually, especially those that relate to control and monitoring (Agarwal et al., 2016) and the construction phase is today often overlooked when it comes to digitalisation (European Construction Sector Observatory, 2021). On construction sites today, great amounts of data are created but much of it are not collected and even less are analysed (Agarwal et al., 2016). A lot of captured data is needed for control and analysis (Alizadehsalehi & Yitmen, 2019), and it is expected that AI could be used to revolutionise the construction industry using Big Data to digitise many manual administrative processes and improve productivity (Nikmehr et al., 2021; Samuelson, 2021). AI, IoT and Big Data are technologies that could be especially useful in the production process if connected to automation technologies (Samuelson, 2021). Drones can today be used to collect data to monitor progress, survey maintenance needs and security, map and create 3D models of sites, do initial surveys and take measurements, do risk assessments, reach areas that are unsafe for humans and transport gods (European Construction Sector Observatory, 2021).

In a construction project many things are happening that need to be monitored in order to accurately adjust and predict the economy and the time plan as well as keep the work site safe and effective (Alizadehsalehi & Yitmen, 2019). Progress monitoring is a very important part of construction management (Mahami et al., 2019; Navon, 2005; Zaimi et al., 2006). Detection of changes and disruption in the project process can help identify mistakes early and give the project the possibility to address those mistakes as early as possible to reduce many types of costs. The longer an error takes to detect, the more costly and harder to correct it becomes (Josephson & Larsson, 2001; Navon, 2005). It is therefore important to monitor the progress of a project effectively. Despite other technological advancements in the industry, control processes are currently still measured and monitored manually (Mahami et al., 2019) by daily or weekly reports of activities performed. Here errors can happen before the data is analysed or in between the reports which makes it hard to rely on this system (Puri & Turkan, 2020). Manual methods of progress monitoring, when they are done in time, are also labour-intensive tasks that are time-consuming, expensive, ineffective, and prone to errors (Alizadehsalehi & Yitmen, 2019; Elazouni & Salem, 2011; Olatunji & Akanmu, 2015; Puri & Turkan, 2020).

2.3 Possibilities in digital technologies

Due to the large part the construction industry plays in the economy even a small improvement would create great benefits for the economy and the value chain and drive the creation of even more positive changes throughout the industry (European Construction Sector Observatory, 2021; Nikmehr et al., 2021). Agarwal et al. (2016) present five ways or trends for which the construction industry could develop over the next few years to meet the needs and challenges that the industry faces. These five steps were "*higher-definition surveying and geolocation*, *next-generation 5-D building information modelling*, *digital collaboration and mobility*, *the internet of things IoT and advanced analytics,* and *future-proof design and construction*" (Agarwal et al., 2016, p. 4). These five steps are all technologies that the industry is studying and are doing tests on, and they are made to interact with each other to create an eco-system with other technologies (Agarwal et al., 2016). Bosch-Sijtsema et al. (2021) also argue that there is a need to look at technologies in the construction industry as a part of a bigger eco-system rather than as separate entities in order to address the fragmentation that the industry is characterised by. Other industries have developed further and can see the benefits of these technologies (Bosch-Sijtsema et al., 2021). For the construction industry the positives that are to gain from these technologies are crucial for achieving successful projects due to the narrow margins and competitiveness that characterises the industry (García de Soto et al., 2019). Bosch-Sijtsema et al. (2021) recommend that when developing technologies in the construction industry there is a need to look at how other, more digitalised industries, have done (Bosch-Sijtsema et al., 2021).

AI can be used together with drones and IoT to collect large amounts of data in real time to analyse and create a digital picture of the live production, a so-called digital twin (Frank et al., 2019). This supports the system in making intelligent decisions using real-time data (X. Xu et al., 2021). Other industries have embraced these technologies and are working with satellites and drones to capture images and sensor input data to follow changes happening in their processes (Agarwal et al., 2016; Kumar et al., 2018; Said et al., 2021). Progress monitoring is something that, when it is done well, have a lot of positive benefits. The most cost-effective and efficient way to perform progress monitoring and change detection is, according to Alizadehsalehi & Yitmen (2021) to automate the process. Other industries such as mining, agriculture and solar industry use automatic, technical solutions to detect errors in their operation. This has proven to increase efficiency, reduce errors and increase quality(Doddamani et al., 2020; Kumar et al., 2018; Said et al., 2021). Automation of these processes are of great importance to the construction industry and the progress monitoring process in order to improve the construction process and reduce costly errors (Alizadehsalehi & Yitmen, 2019).

2.3.1 Drones to capture data

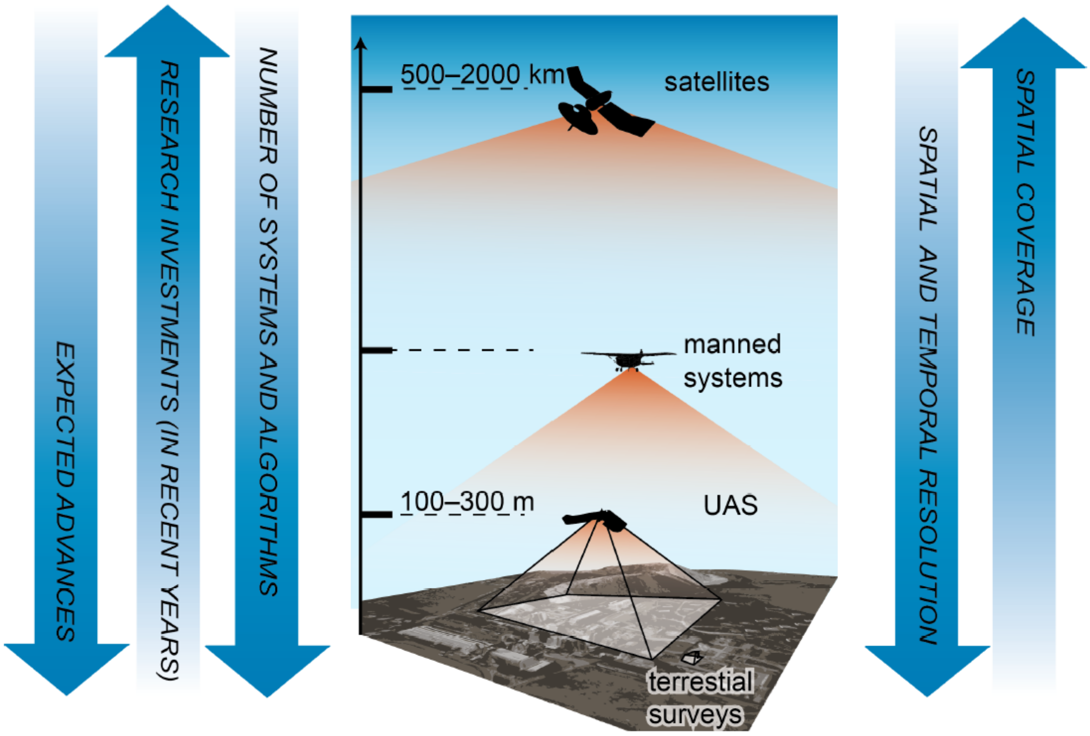


Figure 2: Comparison of the most important aspect of spatial data acquisition (Jeziorska, 2019).

There are different physical systems used for monitoring an area from above, an activity that is also called remote sensing. These are satellites, manned aircrafts and drones. Figure 2 shows the conditions for the different methods where UAS, which stands for Unmanned Aerial System, is the system that includes drones, as mentioned also called UAVs (Greenwood et al., 2019; Jeziorska, 2019). Satellites have a large range and can cover very large areas. They are also the method most invested in, but it also has the lowest resolution. Drones have a much higher resolution but cover smaller areas and has a lower area of research. The manned aircrafts are in between these two systems in most aspects but they also need manned personnel on board. Drones are with their expected advancements and large number of algorithms and systems as well as their high resolution (Jeziorska, 2019) the most ideal system for progress monitoring through change detection in the construction industry.

Drones can be defined as *"aeronautic platforms that operate without the use of onboard human operators"* (Greenwood et al., 2019, p. 1). These are most suitable for smaller areas (Jeziorska, 2019). There are three types of drones: rotorcraft drones that can have three, four, six or eight rotors; fixed winged drones that work similarly to conventional airplanes; and Vertical Take-Off and Landing drones (VTOL) that are a combination of the previous two but are rarely used. Fixed wing drones are ideal for covering large areas and collecting large amounts of data in lower resolutions. Rotorcraft drones are flexible in their flight patterns and can stand still and hover in the air (Greenwood et al., 2019; Otto et al., 2018) which makes them ideal for data collection in complex environments requiring precise movements and mapping of 3D features (Greenwood et al., 2019). They are, however, very affected by weather conditions, especially wind. They have a limited payload and can usually not carry that much weight. The same goes for their range of flight or time of operation. Most drones have an on-board power supply that will run out and require the drone to land and have the power resupplied. The drones also must have a stable connection to a ground station in order to navigate and send information and there are many things such as buildings and transmission lines that can interfere with that. A drone may also have limited memory capacity for data collection. Many countries also require a human operator to plan and monitor the drone's journey and the data it collects (Otto et al., 2018) and Sweden is one of them (Transportstyrelsen, 2021; Vesvre & Sandén, 2019).

Drones can reduce costs for labour and operate in environments with low safety. As they do not need an on-board pilot or any of the equipment that requires, which means they are lightweight and therefore they have a low cost and use less energy and are thereby better for the environment. They can access dangerous and remote areas that humans cannot or should not be working in. They also do not require road infrastructure to move around (Otto et al., 2018). Flight planning is used to plan the route the drones take while flying and sometimes that is complemented by an obstacle avoidance sensor (Bognot et al., 2018; Greenwood et al., 2019; Moeini et al., 2017). Drones are most commonly navigated by Global Positioning System (GPS), and some have even started using Real Time Kinematics (RTK) which uses differential measurements from GPS to achieve a higher accuracy (Jeziorska, 2019). There is also something called a Ground Control Station (GCS) or Remotely Piloted Vehicles (RPVs). A GCS is located on the ground and provides location, orientation and information about connected systems through constant input information (Jeziorska, 2019).

2.3.2 Sensors for data collection

Drones can be equipped with many different types of sensors. There are RGB colour cameras, laser scanners such as Light detection and ranging (LiDAR), hyperspectral cameras, multispectral cameras, and thermal scanners (Jeziorska, 2019). The RGB cameras capture images from light in the visible spectrum so that the human eye can look at and understand the data. This is the sensor that is mostly used for monitoring, and it is also the most affordable (Jeziorska, 2019). The use of cameras relies on good lighting and weather such as snow and sandstorms and rain. The camera is also comparable with the human eye which means there are no advantages in resolution and the result is presented in 2D. Advantages of cameras is that they can identify colours and shapes and recognise types of objects (Autocrypt, 2021).

LiDAR is a common method when examining the surface of the Earth. It sends out a laser pulse to measure distances and create 3D models of an environment (NOAA, 2021; Velodyne Lidar, n.d.). The data is presented in black and white and there are different types of lidar that can also detect the floors of areas of water and do land mapping (NOAA, 2021), however, these are too heavy for drones. The issue with weight applies to many types of LiDAR which means that there has to be a choice between performance of the sensor and the quality of the drone as it has to give up weight to accommodate the sensor (Jeziorska, 2019). LiDAR also require a large amount of computer power and is more expensive than cameras (Autocrypt, 2021). Since LiDAR is its own light source, it does perform well in the variety of lightning and weather conditions (Velodyne Lidar, n.d.). They are also very accurate and can detect very small objects as well as identify the type of object. It is very efficient as it takes a lot of measurements during a short period of time (Autocrypt, 2021). LiDAR is used in some industries today in combination with drones (Petkovics et al., 2017; Said et al., 2021) and it is also predicted that LiDAR will become more common on drones in the future (Jeziorska, 2019).

Multispectral cameras are cameras that can capture light in both the visible and invisible to the human eye (Jeziorska, 2019). It measures energy that is reflected within several specific section in between three and ten different spectral bands. Hyperspectral cameras work similarly to multispectral cameras, but it can collect data in up to two hundred spectral bands (MAPASYST, 2019). The data these technologies collect is very rich and can even identify the condition of vegetation (Doddamani et al., 2020) and distinguish different materials (Yang et al., 2018). The more sophisticated the system the more expensive and the bigger and heavier it becomes. The large amount of data these generate are also hard to handle (Jeziorska, 2019). Furthermore, data with more spectral bands is better at identifying differences (MAPASYST, 2019).

2.3.3 Data processing and management

Images collected by drones can be combined into orthophotos using photogrammetry (Said et al., 2021). Photogrammetry is the act of creating comprehensive information by deciding distances and identifying positions of objects together with characteristics like size and shape of objects. When a drone takes two images with a certain overlap, objects on the map will be seen from different angles. With the help of measurements of these objects, photogrammetry calculates three-dimensional positions of points that can be used to create 3D models, maps, hight models and orthophotos. Orthophotos are geometrically corrected aerial photos with reduced height differences and works as an informative geometrical map suitable for measurements (Harrie et al., 2013) and visualisation (Jeziorska, 2019). Height models are also called point clouds, and these are three-dimensional models of structures and environments often created using data from images or laser such as LiDAR (Harrie et al., 2013). Point clouds that have been created from drone imagery can help progress monitoring on the construction site. This can, for example be done by comparing a point cloud with a BIM model (Jacob-Loyola et al., 2021). Working with photogrammetry require a lot of computer power and memory and the same goes for then analysing the data that has been created using methods such as machine learning (Calo et al., 2017; Harrie et al., 2013). This is why the concept of Big Data is important to consider.

Big Data is *"the collection of huge amount of digital raw data that is difficult to manage and analyse using traditional tools"* (Jan et al., 2019, p. 1). These data come in different shapes, formats and sizes and are complex to handle. Big Data can be found in many industries, and it is important for these industries to know how to handle all this data (Jan et al., 2019). For the construction industry this can, for example, be data collected by drones and other monitoring devices. Remote sensing data is complex and often comes in large quantities with big variability (Ma et al., 2015). Images, for example, is a large issue due to the sizes of the files. Big data creates challenges when it comes to data analysis and streaming, reliability in analysis, quality of data and storage to name a few (Jan et al., 2019). The volumes and variety of the data as well as the speed the data needs to be processed in require new methods of processing as the traditional ones does not measure up (Özdemir & Hekim, 2018). IoT is one area where Big Data is a big issue, and it can be defined as a *"hyperconnected computing environment"* (Özdemir & Hekim, 2018, p. 67) with many interconnected devices that can be *"any application monitoring and optionally manipulating a physical environment"* (Calo et al., 2017, p.1). These systems generate large amounts of real-time data that need to be processed. AI reach many problems related to Big Data when applied to systems of the IoT (Calo et al., 2017). It is therefore important to consider Big Data when creating AI systems for change detection of drone-captured data as drones can be connected to the IoT (Goudarzi et al., 2019; Shi et al., 2020).

Recent technical developments have created IoT sensors that can capture massive amounts of data and these data must be processed and analysed efficiently to be used for decisions and applications (Wu et al., n.d.). Handling Big Data that the drones collect require a lot of computer power (Calo et al., 2017; Shi et al., 2020). To be able to handle those amounts of data there is a need for systems that can work quickly and simultaneously (X. Xu et al., 2021). Central Processing Units (CPU) and graphics processing units (GPU) are two processors that are used to process data. A GPU can be used to process Big Data because of its advanced feature and fast processing. It can complete computer task efficiently and simultaneously and are thereby suitable for image processing (Jan et al., 2019; Lee, 2020; Ma et al., 2015). Parallel processing is the processing of multiple datasets simultaneously using different cores. It breaks down the data into separate parts and can therefor process multiple datasets over a shorter period of time (Lee, 2020). Large-sized data, especially images, usually have to be processed in smaller blocks but that can put pressure on the device that does the computing, especially if that device is used as an edge (Shi et al., 2020).

Edge computing is meant to relieve a system by pushing the computing task to the edge of networks to reduce the data that is transferred between devices. An edge thereby processes information close to or at the data source and then send only the relevant data further, increasing performance and creating better response times and reducing energy consumption (Wu et al., n.d.). An issue with this is that the large amount of processing power that is necessary when handing Big Data is not always available at the edge (Calo et al., 2017). Drones can be used to collect data efficiently in an IoT and, if they are connected to a cloud, they can send information to an edge that processes the information and gives real-time feedback (Goudarzi et al., 2019). An edge can also help reduce costs for data processing and to increase privacy as data is processed in one location before being distributed. The last issue is especially relevant when looking at drone-captured images that may contain sensitive data (Calo et al., 2017). However, to be able to effectively use edge computing, parallel processing, IoT and GPUs there is a need to look at and understand AI and machine learning (Calo et al., 2017; Lee, 2020; Shi et al., 2020; Wu et al., n.d.).

2.3.4 Artificial intelligence and machine learning

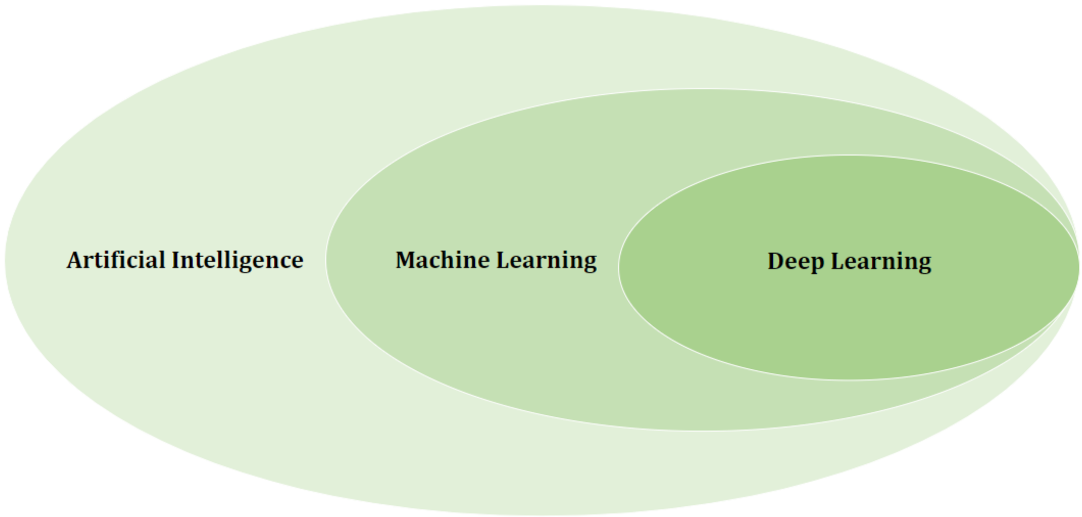


Figure 3: The relationship between artificial intelligence, machine learning and deep learning.

Artificial Intelligence (AI) is *"the science and engineering of making intelligent machines, especially intelligent computer programs"* (Stanford, n.d.). AI is a field concerned with understanding intelligence and replicating that intelligence in computers (Human-Centered AI, n.d.). Many technologies that are used today are parts of AI or use AI to some extents. Computer vision, optimisation and robotics, such as drone, are some examples of those types of systems (Abioye et al., 2021). AI and robotics can do mundane and repetitive tasks, relieve workers of heavy or dangerous jobs and reduce the risk for mistakes (European Construction Sector Observatory, 2021; Özdemir & Hekim, 2018). There are multiple subcategories of AI that has different types of capabilities and degrees of complexity. These can be seen in Figure 3. Moreover, industries such as agriculture, heath care, climate and remote sensing have started using AI effectively and developing their work methods (Human-Centered AI, n.d.; Khelifi & Mignotte, 2020). Also, the construction industry has started to realise the benefits of AI and are working on ways to use it in their operations (Abioye et al., 2021). In construction AI have proven to increase productivity, safety, and profitability as well as helping to detect possible clashes, delays and changes (Abioye et al., 2021; Schober, 2020). AI have also shown to be able to monitor the whole value chain from the pre-study stage to the facility management including design and production. Here AI have been able to help keep projects on track within time-limits and budget (Schober, 2020). As mentioned, are drones a system that use AI. For collecting images for change detection, the use of AI refers mostly to the flight path and collision control (Petkovics et al., 2017). Subcategories of AI in Figure 3, such as machine learning and deep learning are used for the change detection process that take place after the data is collected.

Machine learning is *"the study of computer algorithms capable of learning to improve their performance of a task on the basis of their own previous experience"* (Mjolsness & DeCoste, 2001, p. 2051). Machine learning covers concepts such as nonlinear regression, data clustering and neural network classifiers (Mjolsness & DeCoste, 2001). There are two ways of training algorithms using machine learning, supervised and unsupervised learning. In supervised learning there are trained data algorithm sets which the system is expected to learn to recognize, once this is done the performance is exposed to other data of similar format for example test sets. In supervised learning there are trained data algorithm sets which the system is expected to learn to recognize, once this is done the performance is exposed to other data of similar format for example test sets. While supervised learning is good method for high accuracy done by manually labelled samples, it is more time consuming, especially for complex projects meanwhile unsupervised learning are generally low in performance but performs well without having knowledge from before as it does not require a lot of labelled training data (Kersting, 2018).

Deep learning, as seen in Figure 3, is a more sophisticated and deeper subcategory of machine learning (Middleton, 2021). It helps to automatically find patterns and identify unsupervised data, without involvement of humans. Deep learning can be used to handle Big Data, extracting useful information from large quantities of data (Jan et al., 2019). A large part of deep learning is the creation and training of neural networks. Neural networks are inspired by the human brain, imitating the complex structure on neurons where the algorithm copies how the signals are processed and transferred (Bishop, 1994). Neural networks are built on three types of layers. One input layer, multiple hidden layers and one output layers where every node in each layer are connected to every node in the next layer. These networks are trained by a lot of data to become more and more accurate. They are very powerful AI tools working with high speed and accuracy and are ideal for image processing (IBM Cloud Education, 2020). There are different types of neural networks that are comprised of different types of layers and are used for different types of tasks (IBM Cloud Education, 2020; Shi et al., 2020). Some of the most common types are Convolution Neural Networks (CNNs), Recurrent neural networks (RNNs) and Generative adversarial networks (GANs) (Bishop, 1994).

Transfer learning is a concept in deep learning that is commonly used when training neural networks. To create a neural network with high accuracy it requires a great amount of training data (Nath & Behzadan, 2020). Instead of training a network from scratch, using hundreds of thousands of images, it is possible to transfer learnings from another neural network by reusing a pre-trained model with new training data. This can be done by removing a few layers from the model and retraining these layers on a limited set of new data that is applicable on the task at hand. Transfer learning is commonly used in computer vision. Computer vision is the science of training computers to identify and categorize objects in visual data in the way humans do it with their eyes. Today, there are studies that show that the system is better than humans in detecting objects as models for deep learning allow machines to more specifically specify and classify objects quickly. Drones are one of many areas where computer vision is used. Here it is often applied to tracking movements or identify objects. The large amounts of data that drones create have led to the need for applying deep learning into solving complex tasks (Khan et al., 2018). Just as for computer vision, also change detection is an imaging processing method that uses different types of deep learning concepts (Khelifi & Mignotte, 2020).

2.3.5 Change detection

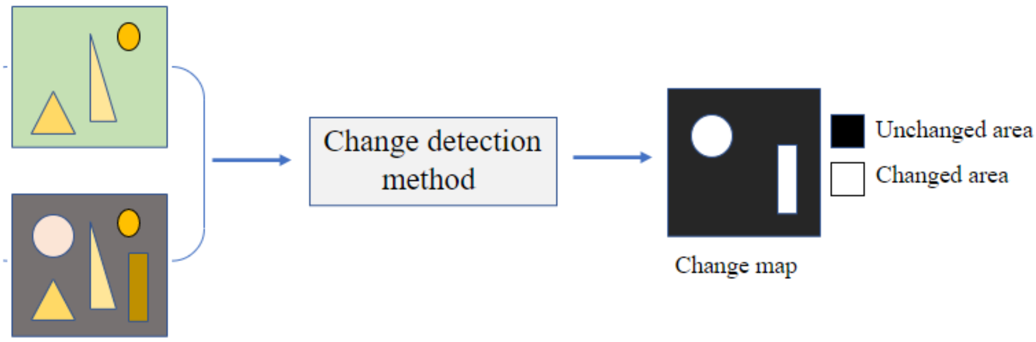


Figure 4: Graphical illustration of change detection inspired by Khelifi & Mignotte (2020).

There are many types of physical changes that can be detected. All of them with different degrees of importance. Depending on the change that needs to be identified different levels of detail is of interest. The change can also be useful to some people or disciplines and not to others. *"Context and perspective are important in evaluating the relevance or importance of any particular change"* (Woodcock et al., 2020, p. 2). In order to be able to monitor change it is important to know how to characterise it. Change can be abrupt, like effects of weather, or gradual, like erosion, but it can also be a mixture of the two or something in between. Change can also be transitional or conditional where the first one is change happening due to fundamental transition, such as the construction of a new building or deforestation, and the second one is when the change comes from difference in conditions, such as water stress on structures and forest degradation. Depending on the frequency of measurements there are also different types of changes that can be detected (Woodcock et al., 2020). Drones can fly very often and can therefore achieve very high temporal resolution (Jeziorska, 2019). These is a balance there as high spatial resolution, detail level, generate a lot of heavy data which reduces the possibility to measure frequently and therefore reduces the temporal resolution (Lu et al., 2004).

When working with change detection it is assumed that something has changes between two different points in time and the aim is to identify that change (Woodcock et al., 2020). Change detection can be defined as *"the process of identifying differences in the state of an object or phenomenon by observing it at different times"* (Shi et al., 2020, p. 1). According to Lu et al. (2004) and Roysam et al. (2005) change detections are used to detect key changes but also needs to reject unimportant and irrelevant ones (Lu et al., 2004; Roysam et al., 2005). There are many different types of change detection algorithms. Changes can be identified on a pixel level, object level, scene level or 3D-object level and some examples of analysis methods are classification and neural networks (Shi et al., 2020). Figure 4 show the principals of change detection. Two input images taken of the same area or, in this case figure, are compared using a change detection method. This method identifies the changes and sends out a result in the form of a change map showing the differences between the images with white and the areas with no change in black (Khelifi & Mignotte, 2020).

In order to use data collected in remote sensing the data needs to be without much interference such as clouds and snow (Woodcock et al., 2020). Noise in data needs to be identified and excluded from the results (Shi et al., 2020) and objects that are not relevant also needs to be handled. For example, when building a road in an infrastructure project there can be vegetation and cars around that are not relevant to the construction of the road (Han et al., 2021). Vegetation growth, difference in sunlight and shadows are issues that need to be addressed (Khelifi & Mignotte, 2020). Pre-processing of data is therefore important in change detection (Hasanlou & Seydi, 2018). It is the process of reducing uncertainties and interference in the data which is meant to reduce errors in an analysis (Shi et al., 2020). This includes aligning images to the same coordinate system and matching spatial resolution and adjusting lighting conditions (Roysam et al., 2005). Feature engineering is the process of taking raw data and constructing features that can then be analysed. This is necessary in even the most sophisticated change detection methods to achieve high performance (Jan et al., 2019).

Object detection can be defined as *"localizing an object in an image and classifying the region into one of the pre-defined categories"* (Nath & Behzadan, 2020, p. 2). To recognize and identify objects such as peoples, cars and cats, for example. There are models that can detect and classify handwritten numbers in images and that can classify thousands of images or objects (Nath & Behzadan, 2020). In order to use object detection, the models must be trained on large amounts of data and that training data needs to be collected from different sources to create diverse datasets for objects that can look slightly different from each other (Hasanlou & Seydi, 2018; Nath & Behzadan, 2020). Many industries have multiple large datasets available to use for training, but they may not be relevant to the construction industry. There are a few datasets specific to the construction sector but none large enough to accurately train models for object detection on construction sites (Bognot et al., 2018; Nath & Behzadan, 2020).

2.3.6 Drones, AI and change detection in industries and research

Many industries use drones, remote sensing, or change detection in their operations. The construction industry is one of them but there are also other industries that utilise these types of technologies and that haves reached further in the development. Industries such as military, agriculture, transport, energy, mining, environment and conservation, and land and oceans observation are some examples. Some industries collect their data using satellites or flights and some use drones. The detection of change is also done with different methods and models and for different purposes (Goudarzi et al., 2019; Higuchi & Babasaki, 2017; Otto et al., 2018; Rogan & Chen, 2004; Said et al., 2021).

One industry that has used both drones, remote sensing and change detection is the solar industry. Some issues the industry have with their solar panel is that they become damaged, that shadows from structures are cast on them or that they become covered in debris. This can cause low power generation and there is a need to monitor this to keep the efficiency of the panels up (Higuchi & Babasaki, 2017, 2018; Kumar et al., 2018). To detect, for example, broken solar panels, there are different methods to use. This could be done by manual visual control, magnetic field assessment in the panels, or by using drones equipped with thermographic cameras. The latter one method has proven to be most effective due to its low time consumption (Higuchi & Babasaki, 2017). This is also highlighted by Higuchi & Babasaki (2018) which talked about the combination of thermographic cameras on drones and deep learning applied to automatic detection. The reason why thermographic camera detection is superior for solar panels is because of its understanding of heat differences and can therefore inspect for example shadows on a panel and thereby locate where the failure is. The automatic detection is done using deep learning and CNN (Higuchi & Babasaki, 2018) and the drones are useful for these purposes because of its monitoring and observation capability and their efficient data logging and collection abilities. They are also very easy to control and the level of detail that monitoring solar panels require is easily provided by drones (Jeziorska, 2019; Kumar et al., 2018).

Agriculture is another industry that uses change detection in remote sensing. Here they collect data with either drones or satellites and use these data to identify and monitor plants and their conditions, animals and their movements, and damages on machines (Minu & Shetty, 2015; Petkovics et al., 2017). Depending on the type of changes that need to be detected either drones or satellites can be most suitable. This is due to the balance between the need for high resolution and the need to cover large areas (Jeziorska, 2019; Minu & Shetty, 2015; Petkovics et al., 2017). RGB cameras, hyperspectral cameras and LiDAR are some of the most used collection methods in agriculture (Horstrand et al., 2019; Petkovics et al., 2017). Depending on the camera's resolution and the data it collects, it can detect different things, for example it can identify small creatures like pests as well as nutrient deficiencies in plants (Petkovics et al., 2017), but it can also detect changes in large agricultural plantations (Minu & Shetty, 2015). Therefore, there might be need to consider combining different sensors to get a better and more covering overview and analysis, especially as there are cameras that can detect objects better than the human eye (Petkovics et al., 2017).

In mining the drone has been used to capture real-time data to monitor hazards, changes and progress. Mining is a dangerous industry with a high rate of fatalities and many risks. Drones can be used to monitor environments to detect changes and dangers before they happen as well as to take over certain tasks in dangerous areas (Said et al., 2021). Another advantage of using drones with change detection is to facilitate a safe working environment by monitoring areas with risk for collapse, among other things. The drones are equipped with good LED light that can capture good images with cameras and stabilisers. This means that they can access and explore remote and hidden areas together with creating models and maps of the mines to use for planning. The reason drones are used in mining is because satellite images do not always have the best resolution when looking at open mines, and sometimes have a frequency that is too low. LiDAR, digital cameras and thermal infrared cameras are commonly used in these types of industries. The drones usually navigate using GPS but in deep mins the connection to these kinds of systems is poor (Said et al., 2021).

When it comes to land-cover and land-use, change detection is highly relevant to implement because those types of areas require a lot of monitoring and managing. With the help of remote sensing and image processing it is possible to detect changes in use and coverage of areas on the earth (Rogan & Chen, 2004). The concept of monitoring land-cover is also helpful for observing societal and environmental changes such as city expansion and ecological damages (Lv et al., 2021). Different sensors that can be used for this is digital cameras, LiDAR and radar. In the monitoring process there need to be trade-offs between different aspects of the result. If, for example, higher temporal resolution is required there might have to be sacrifices in spatial resolution. In this case, it is important that the dataset is selected carefully alongside with the technique that are used to process the data. Depending on what methods are used, different types of training data can be needed (Rogan & Chen, 2004). Another area where change detection is used is the monitoring of land surfaces to detect changes in ecosystems (Woodcock et al., 2020).

The interest of using drones in the construction sector is increasing. Drones are able to collect data with higher accuracy and efficiency and to a lower cost than any traditional methods in the construction industry (Elghaish et al., 2021). It is even possible that infrastructure and construction is the industry where drones have the most potential in market value out of all industries (Otto et al., 2018). Other applications of drones in construction can be to reach remote areas or high structures and to capture data in the form of photos and maps for use in surveying, security, and mapping (Elghaish et al., 2021; Otto et al., 2018; Zaychenko et al., 2018). For monitoring, safety and inspection drones can be used to reduce the time construction managers and other personnel spend on old-fashioned manual monitoring processes. Drones can do it faster and more accurately than a worker could ever do. Progress monitoring is an important aspect on a construction site and has a large effect on the success of a project. There is, despite this, as mentioned before, a lack of research on drones in construction. This is especially true when it comes to the use in control functions such as progress monitoring and inspection (Elghaish et al., 2021).

In construction there are some pilot projects when it comes to detecting changes and monitoring progress with the use of AI and other technologies (Czerniawski et al., 2021; Elazouni & Salem, 2011; Nath & Behzadan, 2020; S. Xu et al., 2021). AI can help analyse large amounts of data and help with decision making and safety monitoring in the construction industry alongside monitoring of continuous progress assessing building performance (Abioye et al., 2021; European Construction Sector Observatory, 2021; Schönbeck et al., 2020). However, important things that need to be considered when using drones in construction is that the use need to be thoroughly planned as all sites are different, there has to be a plan for what to do with the information after it has been collected. When done well drones can help improve safety, efficiency and accuracy in the data collection (Zaychenko et al., 2018). In construction there are studies on detecting a few limited types of objects on the construction site, but the lack of large datasets is still an issue (Nath & Behzadan, 2020).

Based on the above literature review, there seems to be a gap in research, especially on the combination of drones and AI for change detection in the construction industry. There are a few studies on similar projects but those are on single cases and most studies on change detection in remote sensing are done in other industries. These industries have different conditions than construction, which is a sector with unique needs, and therefore the learnings from other industries are not entirely applicable there. The project-based structure, fragmented work processes and dynamic work processes require special types of digital solutions with.

2.4 Ethics and sustainability considerations

To summarise, there are many challenges that the construction industry faces and the solution to multiple of them are more digitalisations. Detecting changes with the help of images from drones could increase the productivity, decrease number of costly errors and meet the needs of a new workforce that does not exists. However, digitalisation also bring its own challenges. There are multiple technical challenges such as large amounts of data, low digital skill levels, lack of datasets in construction, cost of equipment and lack of research on potential applications (Abioye et al., 2021). There are also some laws and regulations that make implementation of drone technology challenging. Moreover, there are also ethical and sustainability implications that new technologies bring with them (Abioye et al., 2021; López & Mulero-Pázmány, 2019; Ribeirinho et al., 2020).

2.4.1 Laws and regulations of drones and AI

Sweden, and many other countries, tightly regulate its air space (Otto et al., 2018; Sveriges riksdag, 2022). In order to fly with drones in Sweden there is often a need to apply for permission. There are three types of permissions: Open, specific and certified. Open category needs no permission as long as the flights are done lower than 120 metres, away from crowds and using drones lighter than 25 kilos. To fly higher than that there is need apply for permission from the Swedish Transport Agency in the specific or certified category. In addition to these categorise it might also be necessary to get per permission from other authorities, such as the Swedish mapping, cadastral and land registration authority (Lantmäteriet), to have the right to distribute captured data (Transportstyrelsen, 2021). When it comes to drones that are equipped with cameras, there is also the Camera Surveillance Act (2018: 1200) that exists to protect people against undue invasion of personal integrity (Sveriges riksdag, 2018). This means that when flying with drones and collecting data through cameras there are requirements to follow these laws as well as the General Data Protection Regulation (GDPR) when collecting data that can be connected to a person. GDPR regulates what kind of information that is allowed to be collected and how the use and purpose of this information needs to be communicated and why (acciona, n.d.).

2.4.2 Ethical aspects of drones and AI

Both ethical considerations and legal constraints are according to López & Mulero-Pázmány (2019) barriers for implementing the use of drones in civilian applications. With the implementation of drones there is always the discussion of integrity and surveillance (Abioye et al., 2021; López & Mulero-Pázmány, 2019). Large amounts of data are collected in areas where people and businesses reside and act and this can be sensitive for multiple reasons. According to Abioye et al. (2021) there is also the issue of AI making mistakes that can hurt people or that hackers can get a hold of sensitive information that have been digitised (Abioye et al., 2021). There are also the issues of malfunctioning equipment, and the decisions AI might have to make to avoid damage or hurt to some people but then affecting something else. Moeini et al. (2017) thinks that there is a lack of frameworks for accountability when it comes to technologies and the consequences of using those and that this could affect the willingness of industries to adopt digital tools such as drones and AI (Moeini et al., 2017). Managing a large amount of data as well as issues such as distrust of the accuracy and safety of collected data are aspects that make it difficult to implement digital solutions, such as drones and AI, in the construction industry (Bosch-Sijtsema et al., 2021).

2.4.3 Sustainability aspects of technology

Figure 5: The United Nation's 17 Sustainable Development Goals (United Nations, 2015).

To meet today's rising global issues, all industries need to work towards a more sustainable society. The United Nations (UN) have established 17 sustainable development goals (SDGs), that can be seen in Figure 5, which are set to steer the global development into a more sustainable direction by the year 2030. These goals are meant to cover all three pillars of sustainability: social, economic and ecologic (Berawi, 2019). However, according to United Nations (2020), the construction industry should focus on goals number 6, 7, 9, 11, 12 and 13 to align with the UN and contribute to the sustainable development (United Nations, 2020). Berawi (2019) mean that understanding the benefits of a digitized world and working with innovation will help to achieve the SDG targets (Berawi, 2019). From a sustainability aspect, technology can help improve quality and reduce waste in the construction industry (García de Soto et al., 2019). It can also be used to create digital ecosystems that improve performance and reduce emissions (Elghaish et al., 2021). Moreover, according to Said et al. (2021), drones can be used to monitor ecological changes that can help to imply negative sustainability impacts (Said et al., 2021). Drones can find and identify environmental threats early on and give the possibility to quickly address them which can reduce the negative effects (acciona, n.d.). Therefor it is important to invest in technologies as they can be applied to causes that help improve ecologic welfare (Berawi, 2019). It is, however, important to be careful not to trust the technology too much so that more errors occur that are not caught and that has a negative effect on sustainability and productivity (Abioye et al., 2021). For example, can too much reliance on digital tool cause a backlash on sustainability as instead of just replacing activities that are harmful for the environment, technologies are used to perform these activities more often. This would help increase productivity but also increase environmental impact (Ribeirinho et al., 2020).

3 Methodology

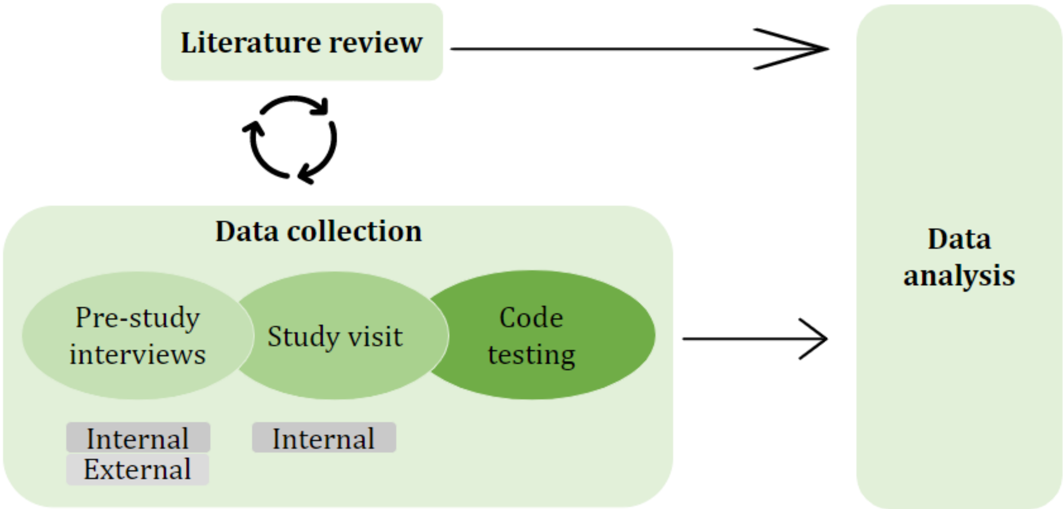


Figure 6: Flowchart showing methodology approach.

According to Bell et al. (2019) methodology is referring to how a researcher is conducting a study based on valid and reliable results that will provide the reader knowledge about the choice of subject (Bell et al., 2019). Figure 6 show the chosen research approach and the following chapters will describe how this master thesis was conducted. It starts with *3.1 Literature review* then followed by *3.2 Data collection 3.3 Image processing, 3.4 Ethical considerations* and *3.5 Reflections about chosen methodology*. The research method is an explorative study with a multi-method approach. The literature and data collection were done abductively with an iterative process between literature gathering, interviews together with study visit, and code testing, to facilitate the exploration that the subject of the thesis required. This helped the authors gain a better understanding of the topic throughout writing the thesis and testing the codes. The study is based on qualitative research with literature and code testing as the primary basis for information complemented by interviews and a study visit. One of the authors possessed some knowledge of programming which made it possible to test the codes without receiving outside help. The aspects of ethical considerations were important when writing the thesis and to give this paper validation and credibility. Finally, this thesis is a collaboration with a large sized contractor based in Sweden, and to not influence the reader with the potential background information they have of the company the contractor will be referred to as Alpha. A discussion of the choice of method will follow in the end of this chapter.

3.1 Literature review

The information assembled from the literature were used to create a background on the topic and to provide information needed to understand the conditions of the industry and the technology. The literature study was also used to find gaps in the research of the topic of drones and AI in construction. By gaining understanding, the help of AI and machine learning in this technology can help to give further knowledge about the subject. The qualitative research method has made that the results from this research are more descriptive than predictive and therefor allows the researcher to draw a conclusion to support the hypothesis or theory being examined (Bell et al., 2019). And gaining knowledge from scientific articles from the industry and AI within machine learning and change detection. The literature used in this thesis were gathered from relevant webpages and databases such as Chalmers library online, Google scholar, Scopus, and ResearchGate.

Keywords: UAVs in construction, Change detection in construction, Drones in the construction industry, Machine learning, Image recognition, Object detection, Progress monitoring.

3.2 Data collection

The data collection was conducted through three steps: (1) pre-study interviews, (2) email communication to municipalities and (3) study visit. This part account for the methods used in collecting and analysing this data.

3.2.1 Pre-study interviews

Table 1: Table with information on interviewees.

Company	Respondent	Referred to as	Participate
Alpha	Project Lead Drones	A1	Interview + Study visit
Alpha	Business Analyst IT	A2	Interview + Study visit
Alpha	Raw Material Supply Coordinator	A3	Study visit
Alpha	Site Manager	A4	Study visit
Alpha	Drone Pilot	A5	Study visit
Lantmäteriet	Team leader	L1	Interview
The municipality of Alingsås	GIS manager	MA1	Interview

To gain some background knowledge of how far the construction industry have come, four semi-structured pre-study interviews was conducted online using Teams and was first held with people internally at Alpha and later externally at The Swedish mapping, cadastral and land registration authority (Lantmäteriet) and with the municipality of Alingsås. See Table 1. The interviews were held during February and May of 2022. Less informal conversations took also place every week over the spring together with an internal focus group at Alpha to facilitate the iterative work process as well as to get feedback on findings, ask questions and discuss thoughts that would occur when more knowledge was gained. This thesis was not based on interviews but rather used a few small pre-study interviews to support the main method of data collection and literature review. In the weekly dialogues that were held, Lantmäteriet and the municipality of Alingsås came up as good examples of actors working with AI in remote sensing and were contacted due to their progress and their role in the construction industry. They work with detection of similar things as other actors in the industry but from a different perspective and it was deemed that their knowledge could be relevant to this thesis. The pre-study interviews were done in parallel with contact via email to about 20 municipalities in Sweden that use aerial photography and drones in the monitoring of changes of their municipality and 10 replied.

The interview questions were not sent in advance to the interviewees, as the pre-study interviews were based on semi-structured natural conversations, however, all the responders were given a brief description of the topic in advance when they were asked to participate in the interviews. The two first interviews were held with interviewee A1 and A2, who both work at Alpha, they also joined during the study visit. The third interview was with interviewee L1, from Lantmäteriet who introduced to what they are doing and how far they have come regarding change detection. The last one was with interviewee MA1 from the municipality of Alingsås, that is one of the municipalities that have come a bit longer in their automation process. All the interviews were approximately one hour long and to fully remember what was said during the interviews, approval was given from the interviewees to record the sessions and later the interviews were transcribed in order to increase the reliability.

3.2.2 Study visit

At Alpha they have been working actively with drones since 2017 and have done tests with drones on a small scale even before that. Today they have a drone department with around 50 pilots in Sweden and adjacent countries and they are collecting data at regular intervals on many of their projects and sites. Therefore, it was suitable to have a study visit in order to see how it works in practise. The study visit at Alpha was made during three hours on a stone quarry site in February with interviewee A1, A2, A3, A4 and A5. The purpose of the study visit was to discuss how the construction industry looks today, which method are being utilized, how the use of drones works, what challenges they face with using drone, and what kind of potential they see with change detection. Apart from that, a tour was made of the quarry to get a sense of the proportions compared to the orthophoto images that they had shown. The A5 also illustrated how the drone is being used outside and talked about how they navigate with the drone.

3.3 Image processing

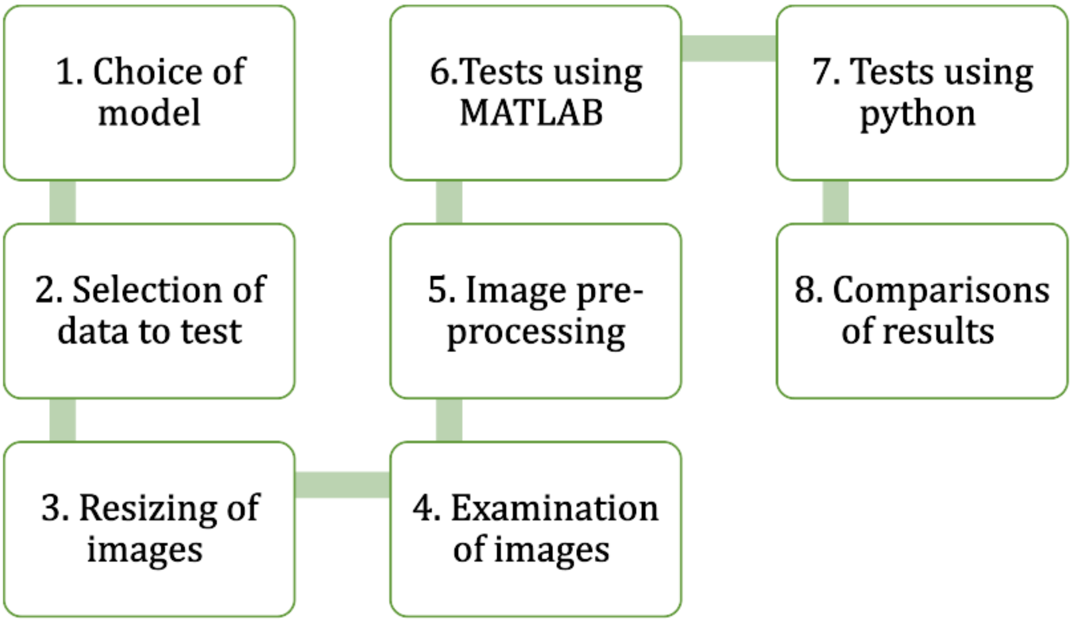


Figure 7: Steps in the process of testing data.

The coding was done using a few chosen methods with code in MATLAB and Python. These two programming languages were chosen because there were many available codes, and the authors had the best knowledge of those languages. These are also two of the most used languages in drones and Python is a very accessible and slightly simple language to learn and follow. The coding was done using the process illustrated by Figure 7 and here will descriptions of each step be presented.

1) The codes that were used for change detection in this thesis were found on GitHub using search words such as *"image change detection," "change detection in satellite images" "monitoring change," "change detection drones," "progress monitoring construction,"* although few of the searches gave many results. MATLAB and Python were two of the programming languages that had the most available codes. The codes were chosen based on what type of data they were created for, how well they created useful results, that they were different in their method, if they needed adjusting due to outdated code or not, and whether the authors had enough knowledge to use them. The first code was run in Python and was a method called k-means and inbuilt Principal Component Analysis (PCA) (Bouzaidi & Ryahi, 2020). K-means is a clustering method that needs no training data and divides the data into groups based on their characteristics (Hasanlou & Seydi, 2018; Shi et al., 2020). PCA is a data reduction method that correlate multitemporal data (Lu et al., 2004; Shi et al., 2020) and are used as a pre-processing method in this model. This method created multiple output images but the 'change map' and the 'difference' image were the ones used in this thesis. The second code was run in MATLAB and was using SAR with a Convolutional Wavelet Neural Network (CWNN) (Gao et al., 2019a, 2019b). SAR stands for Synthetic Aperture Radar and are the type of images used to train this algorithm. It reaches a high resolution by using signal processing (Shi et al., 2020). CWNN is a convolutional neural network where the pooling layer, the layer in the neural network that adjusts the dimensions of the data to reduce the size of output feature maps, is replaced by a wavelet constrained pooling layer (Gao et al., 2019b; Han et al., 2021). The third and last code was run in Python and was based on computer vision using thresholds and dilations. This code was found using Google and can be found on (Stokry, 2021). Here the program analyses one image and identifies distinctive details and then counts what could be called objects which is connected areas of distinct features.

2) The images used in this thesis were received from Alpha and had a size of 5472x3648 pixels. The resolution of the collected data was 1.56 cm per pixel, and they were taken by a drone. The images came from one infrastructure project and one stone quarry owned by Alpha. The images were chosen after if there existed any pairs with images taken at different times that had similar positions, so the comparison could be done and after if there were any interesting characteristics that could be discussed or analyse.

3) In order for the programs and computer used for the tests to be able to handle the images there was a need to reduce the size of the images. Two different versions of each image were created. One with the size 1090x725 that were used in Python and one with the size 1084x721 that were used in MATLAB. This was because the model that was used in Python resized the image and the result came out in a smaller size. To be able to compare the images using change detection they had to be resized to the same size. The code for this was in Python and can be found in *appendix A1* for the Python images and *A2* for the MATLAB images.

4) The examining of images was a process meant to identify characteristics of the input images that can affect the change detection. This were things like shadows or colour differences that could give a false change and objects that could be interesting to observe. This part was also where the final decision on which specific images to use were taken.

5) Four types of image pre-processing and feature engineering was tested on the images in this thesis before going through the models. First, it was the PCA described previously, then making the images black and white, matching the colours of the images to each other, and combining both those with, colour match before turning them black and white. The code for the last three can be found in *appendix B1, B2, B3* respectively.

6) The tests in MATLAB were done in the background over multiple days as they took a long time. Each test took longer than the previous and required a restart of MATLAB after a few rounds to get the time down. Why this worked is unclear. MATLAB was also used to test the difference between the results of the feature engineered images and those that were not engineered as well as comparing the results of the code used in Python and MATLAB.

7) The test in Python was done first but then redone after tests had been done in MATLAB. This was because there was a learning curve to understand what sizes of images that worked and which codes would be suitable. The tests in Python were also performed in the background but during a shorter period of time. In Python the tests with computer vision code were done too and those took only minutes to complete. These tests were also the one done last.

8) The comparison of results was done both by manual ocular analysis and by detecting differences between the results using the SAR change detection algorithm in MATLAB. The comparisons were between the images from the following results:

- Black and white – no feature engineering (Both CWNN)
- Matched colours – no feature engineering (Both CWNN)
- Black and white – matched colours (Both CWNN)
- PCA feature engineering (K-means) – no feature engineering (CWNN)

3.4 Ethical considerations

This thesis has followed four ethical principles of business research, which are avoidance of harm, informed consent, privacy and deception (Bell et al., 2019). As mentioned previously in keeping with the contractor's confidentiality and anonymity and to not influence the understanding of the reader, the name of the contractor will not appear in the master thesis and will thereby be referred to as Alpha. Moreover, before having any interviews, the authors of the paper made sure that all personal communication was kept anonymous and was not shared outside the two authors. However, when reaching out to Lantmäteriet and the municipality of Alingsås, they gave their approval of their organisations to be called by name in the thesis. During the study visit the participants were all well informed about the visit and could choose to participate or not. The privacy of all people involved were respected and it was important that the involved people in the master thesis knew that they could chose to withdraw their statements or participation in any way at any time. When collecting data and images, there was continuous discussion together with the internal focus group and the supervisor to make sure the data was correct, and that Alpha approved of them being used. This was valuable feedback for further development of the thesis.

3.5 Reflections about chosen methodology

The choice to have a qualitative research approach was based on the multiple methods that the thesis required to work exploratively and iteratively. It made sure that when using many different methods, the result could be analysed and compared, and conclusions could be drawn. The pre-study interviews could have been held a little later or multiple times as when the knowledge of the research area grew it would have been possible to ask more relevant questions. However, due to the weekly meetings with the internal focus group, discussion that were also held complementary questions on the subject could be brought up. The study visit was done to get a view of how things worked in real life, and it also made it possible to talk to people that would eventually work with these technologies in the production. More study visits could have been good to do, on different types of sites, or at least some more interviews with people that know the industry and their needs. This could have been especially useful later in the process when some results had been reached to discuss these more in depth and raise the quality. There could have been test with more different types of codes in this thesis. However, as the aim was not to find the ideal model or create a new one, but to explore and test the technology, the amount of testing that was done can be deemed suitable for this master thesis.

Finally, the collaboration between the authors of this paper has been good. In addition, the communication with the supervisor have been of great support in the thesis work, and the internal focus group have also contributed to interesting discussions and analysis together with valuable feedback every week. The approach with frequent internal meetings were suitable and desirable from all parties. Moreover, the authors have been allowing themselves to question each other, support the work, be self-critic. The workload has been equally distributed between the two authors.

4 Result

The result part is divided into three parts. The first part presents the results from the study visit, the internal focus group and the pre-study interviews internally at Alpha. The second part presents the results from the interviews with Lantmäteriet and the municipality of Alingsås together with the responses from other municipalities. The third and last part includes the results of the image analysis and testing of algorithms.

4.1 Pre-study interviews and study visit

The study visit, and the interviewees at Alpha gave a good overview of the uses of drones in the construction industry and issues they are facing now. The following chapters will go through the topics that were discussed. This will start with some background on drones and the technology and then go over issues that they identified to finally look at some expectations they have for drones and AI in the construction of industry.

4.1.1 Application areas for drones

During the study visit and the interviews A1 and A2 discussed that they use drones to create videos for weekly meetings and promotional purposes and to create orthophotos and point clouds to use for visualisation and volume calculations among other things. The flights take place at different intervals but the sites that came up in the interview and the stone quarry, where the study visit took place, were flown around once a month. They also fly manually on some parts of the quarry when it is time to blast to create a 3D image of the mountain side. The collection of data that are done at regular intervals in the stone quarry is mostly manually analysed which takes a long time and there is little point in flying more often when the data cannot be analysed quicker today. The uses of drones are many, according to A1, and many other industries, such as the police, first responders and the forest industry, also work with them in different ways. Drones are an effective way of collecting data and can capture reality in video and imaging well and simple models and images make a lot of difference and has a lot of value. The images and videos have a connection to reality that drawings lack, and they are in colour which makes it easier to understand and connect to real objects. This makes it a lot easier to follow up on production when they can create real-life, real-time models of the actual as-built state of the project and look at it together. It makes it easier to understand for everyone and requires less knowledge about drawings and other traditional materials. When seeing things that are familiar from the physical world, the information becomes less abstract. A1 sees this as a large benefit of using drones. That is makes collaboration easier and more understandable for everyone involved and it heightens the quality of the general work.

Most things that happen on a construction site are reported to the site manager but using drones for change detection is a complement to this that can make sure that nothing is missed. According to A1, if something were to happen that were not planned or not done on purpose or be overlooked there is always a possibility to go back and look at the data that has been collected to see what might have happened. Not to mention that the drone data becomes a confirmation making sure that the right things are done and that the information the manager receives is correct. During the study visit it was also brought up that no information is also information. That the data from the drone that shows that no changes has happened could mean that something that was supposed to happen is now late. Calculating volumes was previously done manually using GPS and scanners. This took a lot longer and required people to walk around on the site putting them in danger. This is a work environment and safety aspect where A1 said that they have seen great value in using drones. Old data from drones can also be used to see where things have been dug into the ground and comparing old images to new ones can show under what parts of the ground things are hiding. A1 also brough up the importance of monitoring the movement of safety and work environment items such as traffic objects and fences. If these move or are damaged it can cause problems for people and vehicles and can cause accidents. This was also something that was talked about on the study visit where they thought monitoring of these objects were one of the most important uses of change detection using drones for that quarry. They also talked about using drones for monitoring the area during blasting in the quarry.

4.1.2 The process of collecting data using drones

In data collection they usually plan a flight beforehand, deciding a day to fly, but weather and temperature of the day affects if it can be done or not. This was also discussed on the study visit where the A5 had to make sure the weather was appropriate for flying and not too windy or too wet. The path of the flight is planned before hand and the flight itself is done automatically using GPS or ground control. A5 is there to manually start the process and change batteries as well as monitoring the drone and the data collection during the flight. A5 also does risk assessment and decide if there should be a flight or if it not suitable. Some drones have a built-in collision control which is more and more common. These systems also make models of the flight area, remembering obstacles and identifying changes in the environment around them creating experience for the drones to use next time it flies. According to A1 it would be preferable if the drone could fly along the ground and not at one decided height all the time as that would create large differences between the images as they are, in some very uneven areas, different distances from the drone and the camera. On the study visit this became very clear as the quarry has height differences of around 80 meters. This was something they were working on implementing with the use of ground models to create a better overlap in the images. When the data is collected, they create automatic orthophotos using photogrammetry as well as point clouds in 3D by generating three-dimensional data using two-dimensional images. Today they use the finished orthophotos and models to make measurements of distances and volumes and use as basis for material orders and progress monitoring.

A1 describes photogrammetry as working with differences in lengths between pixels to determine distances. This is then used to create orthophotos and point clouds using the overlap that the images are taken with. There are some issues with uncertainty of the measurements as the drone data are distorted a few millimetres which they try to address through placing GPS positions in a few places of a site, something that were shown in the study visit. According to A1 technology is changing constantly, and that cameras and other technologies evolve over time which means that images will have higher resolutions in the future and the drones will become better. Better technology will then result in more information and there is a need to analyse this information properly and effectively through automatic processes.

4.1.3 Challenges in implementing and using drones

According to A1, there were a lot of discussions around drones a few years ago. A lot of worry about what they might be used for, and these fears do not seem to have been realised completely even though there is still a long way left in the development. Furthermore, there are, issues that it is important to consider today when working with drones. A1 elaborates that the DJI drones that are made in China, have been regulated in America because it is unclear where the information that is collected end up and who might have access to it. They have to become better at the planning and risk assessment part of using drones. To be clearer about the purpose of the drones and the information they collect and to clarify that they monitor the overall progress and not individual's productivity and movements and that faces of people are blurred. They also need to be better at understanding the risks and how to handle them. Furthermore, to understand and be aware of the existing regulations and to know what the hardware can and cannot do. There are also possible issues of other drones flying over their areas and collecting their information. A1 also clarified that it is important to look at how to distribute and store the results. The limited flight height is another issue that they have to deal with. Right now, they can fly at a maximum of 120 meters without special permission and this limits their ability to capture the data they want, especially in the stone quarry because of the large height differences in the area. The restrictions on flying as well as requirements on good weather can also contribute to a stressful work environment, as the A5 constantly adjust the flight of the drone after the conditions.

Weather is another issue for the use of drones, especially in the form of snow as a site covered in snow is very hard to analyse even for humans. These conditions would require other sensors than cameras. A1 discussed LiDAR as one option that probably would give a better precision than cameras would but also that those sensors are expensive, and the data collected is in black and white. It becomes useful for less people as it is not as easily interpretated as images and videos. However, it could be possible to combine LiDAR or other sensor-data with images to use one method for detecting changes and one method to visualise that change. A1 also said that if it becomes clear that LiDAR is the best option and that it is worth the money then there would hopefully be a development in that. Furthermore, there is much knowledge to gather from studies on satellite data that have been used more and to look at how other industries have worked with similar solutions. During the study visit it was also discussed around the importance of proof of concept so that the decisionmakers want to invest in the solutions because they can see the benefits.

Another large issue that A1 sees today is the massive amounts of data that is created by the drones. The files are large and many and looking at them manually takes massive amounts of time, not to mention the issues with storing all the data somewhere. They have a central cloud-based data storage they use for this purpose and to distribute the information and for everyone to access easily. There is also the issue of knowing when data is relevant or not. To detect structures that are now hidden under ground the data might need to be saved for a long time while changes such as moving gods or temporary structures might only be important for a few days, weeks, or months. According to A1, another important aspect is the ending of information flows. How to decide and what to do when the data is no longer useful and when the point comes where more information is not creating any value. That it is an important aspect to consider when data no longer has a purpose and should be deleted. The data storage that Alpha has creates a lot of information and this rises issues with too much information. When is the data too much? When is it too much to handle? Too much to interpretate. Too much to work with. Especially if they want to increase the frequency of measurements. It would not be sustainable to have people sit and analyse images multiple times a day. A1 thinks that there will come a point where the *"inflow (of information) will surmount humans' commitment"* and means that too much information is a work environment issue.

When it comes to changes, A1 explains that for some roles it could be necessary to fly every other week and for some they need new information multiple times a day. This can also differ from project to project as sometimes very few changes happen if the data is collected too often and in other projects many things happen, and more regular data collections are needed. A1 makes an example of monitoring when they dig into the ground and want to catch what is in the ground before the ground is restored but they also do not want to take the same images too many times. Furthermore, not everyone at a workplace needs to have all information. Different types of data are interesting to different roles, and if everyone get all the information it could lead to stress, and that the important information is overlooked. A connecting factor, that also was brought up, is the uncertainty in the data and when that becomes a problem. When does it become a stress factor that not all data that is collected and the results of analyses are completely correct? Sometimes they find things in the data that they know are wrong and then they start to question the rest as well.

4.1.4 Expectations on drones and AI

According to A1, the goal is to fly more. There is something called drone in a box which is a concept of an automatic drone stored in a box that then opens at regular intervals and does a flight capturing the area to then return to the box charging until next time. Something like that might be the ultimate goal for Alpha: To always have updated data that has been collected automatically and newly created models and maps. It costs a lot but if it were possible, they might even fly once an hour. On the issue with limited flight height and the need to apply for permission, they talked on the study visit about wanting the construction industry to be a separate category for air space. This, they explained, so that they could control their own air space above their projects and sites to have a freer range to fly. In relation to this they discussed that to make this happen there might be need to underline the societal benefits of using drones so that there would be a motivation for the laws and regulations to change. Both A1 and A2 also speculate on the possibility that some activities and processes in the construction industry might have to change to accommodate effective and accurate data collection. A2 gives example on that a good idea could be to implement QR codes by placing them on certain objects and then let the drone find them and detect if they move or change. The great thing with AI is the opportunity to be able to communicate with it, and thus tell it what to do.

At Alpha, they do have similar technologies using AI and analysing images with stationary cameras and robots and these are all technologies that should help improve the industry and that will be worked with more and more. The stationary cameras could do similar things that the drones do but for one place and in more detail and ground-based robots can work similarly indoors. On the study visit they brought up other ideas for using drones such as leading trucks through the area and to detect if people were in the area when they were blasting stones. It was also expressed a desire for a system that could notify the site management of changes that occurred on the site. Specific cases that were brough up was to monitor when safety equipment such as fences were moved or damaged. They underlined that safety is very important and that monitoring of safety equipment and dangerous places and activities are needed in all hours of the day. Another idea for a change detection technique was to measure gradual movements of a slope they had to see how much it changed over time and assess risk for landslide. A2 also underlined the importance of image processing to normalize the images and make them more easily interpretable for the AI. Examples was to make them black and white or increase their contrast so that some shadows may disappear.

Both A1 and A2 agree that there is lacking a national model registry for items used in the construction industry. That there is a need for a place to access data on items that are commonly used on a construction site so that this can be used to do object detection. That there is a lack of datasets and object libraries to train models to detect objects in images of construction sites. Some objects such as fences that are very thin and hard to see from above are also hard to detect using drones. Another problem is that identifying and following construction tools such as machines and trucks to monitor their progress would require a service catalogue with these objects that can be used to train a model for this purpose. A2 also believes in a combination of different methods such as object recognition and change detection could be preferable for detecting changes. Edge computing is another thing that might be necessary, where they can process certain things locally, for example, in the camera or drone itself which does some of the processing and then send out only the result. The changes could be detected in the edge and then instead of sending all information to data storage and further processing they can send only the relevant changes. By doing so, the amount of data that needs storing and further processing is reduced and sensitive data protected by GDPR are processed before reaching external platforms. Another aspect that came up, regarding the large amounts of data, was that it might be a good idea to process the data in different steps. Starting with a low-resolution analysis of the entire orthophotos to identify areas with changes followed by a more detailed analysis of the areas with changes. Edge computing could also help with privacy aspects as the processing of blurring faces can be done in an edge before data is shared.

Both A1 and A2 agree that at present there are some hinders to work further on when it comes to detecting changes. A2 ends the interview by explaining the need for new roles, knowledge and people who can take the time to further develop the use of drones and especially in combination with AI. There will still be a need for people to monitor the use of AI and verify that the results are correct and that the models are being used in the most appropriate way. Finally, there is a need for decisions around the management and administration of these systems. To decide who will be responsible for the reliability of the processes, data and verification.

4.2 The use of drones and AI at other stakeholders in the sector

There are other stakeholders that at present uses drones as well, the same goes for the clients and thereby end-users too. To be able to make decisions early, it can affect the clients process, therefor there is a need for technology early on in this stage. Public clients use of drone can be found in Lantmäteriet, as well in some municipalities in Sweden, one of them who have come a bit further in using AI and machine learning, is the municipality of Alingsås. Other municipalities that used drones, have all almost jointly answered that the drone is not used today to automatically find changes. They use it to only take aerial photos manually and then look at these pictures and insert them into their system manually. However, most of them have expressed an interest that it would have been good to be able to apply such an automatic system. Moreover, what can be understood by the findings of this chapter is that the value of this automatic process lies within the end-user, the demand and request of the users.

The Swedish mapping, cadastral and land registration authority (Lantmäteriet) has, according to L1, during the past three to four years, started working with AI and automatic analysis of their collected data. Today they fly with aeroplanes over Sweden and collects images of a third of the country each year on going, in order to see if their documented buildings and facilities match the reality or if there are buildings that should not exist but does so any ways. This takes a lot of time as there is a lot to go through and they have today up to 150 people that does this. There are thousands of images and a large part of the staff, administrators, and so on, sit and work with these images and try to update the topographic data. One of the reasons they want to implement AI is to speed up this process. As of now, they have implemented machine learning in their process towards becoming more automated and are, at this stage, able to detect buildings. At this point they only detect if a building is there or not while measuring of new buildings still need to be done manually because it requires different knowledge and other data to be able to work with it However, by incorporating machine learning with their manual work, they can get help with finding the changes that has happened and this means that they do not have to spend time looking at every image.

Of Sweden's many municipalities there are some who work with drones to collect and sometimes even analyse geographic data. Among the ones that were contacted some had drones but did not use them and most of those who did use them did not have an automated process for analysing the data. However, almost everyone answered that they had plans to automate or thought such a solution would be beneficial. They could see how using AI could benefit their work and make it more efficient and accurate. There were also a few municipalities that had started this process, Alingsås being the one that seems to have done most. Most municipalities create their maps manually using different software, but everyone seems to want to go from a manual process to a more automatic one but as of now few have started such a process. For most municipalities, the regularity of updating the orthophoto set was ones a year or every other year, was found sufficient to detect new buildings, alterations and demolition as well as ground details. While most of the municipalities did not have any automated processes for their collected information in place, one municipality answered that they had calculated the number of parking spaces in their area by using AI based object detection on cars in their orthophotos. Alingsås municipality claimed that their municipality has come further than most and has started to investigate possibilities of utilising AI for analysing their data. MA1 explains that today they use orthophotos throughout the municipality as aids in map services and for decision making. However, they spend a lot of time on manual monitoring based on this data and they wanted to find a better solution to save time and thus be more effective. Today, they only have one person who spends around 400-500 hours a year to work with this. They also want to fly with drones more as today all their orthophotos are taken by flight and Alingsås are constantly looking for new and smart development opportunities in drones. Therefore, now that AI has grown and its usefulness is clearer, the municipality also want to take part in the development.

At Lantmäteriet they are working on three different projects regarding AI in remote sensing. The first on is that they have started to work with open-source code that they use to identify buildings in their images. This process has already passed the test stage and they are now moving on to get this into production. The next step is to try to detect roads, power lines and ground covers. In the second project Lantmäteriet use a platform called ESRI where they have finished algorithms that they use to detect everything from buildings and ground covers to seabed. The third project that they look at is using satellite data to analyse changes to get a complete picture of the entire country. Right now, operators look at a lot of data where nothing has changed, and they want to narrow down the amount of data that needs to be reviewed with the help of automatic analysis so that areas of no change are sorted out before manual processing. Lantmäteriet collect data and provide it as a product, but they cannot today guarantee that the product is kept up to date. At the municipality of Alingsås they have just finished a project on detecting areas and some objects in their orthophotos. This project included identifying roads and other hard surfaces, vegetation and open ground, water, and buildings and calculating their areas.

Lantmäteriet has certain training data that they set up where they have picked out a number of areas that they have labelled and then used to train the algorithm to improve their models and pick up more changes. Sweden differs a lot in seasons and building style through the country which requires local data to train the models. Other factors can also interfere, like for example resolution, some fly with 15 centimetres and others with 40 centimetres. More differences in resolution mean more differences in variables and hence in the identification itself. Another example of problems that they have seen is in Norway they cannot see their cabins from above as they are often covered with grass and the algorithm cannot identify them. However, comparing manual identification with AI they both achieve similar accuracy but the more training data they have the more accurate the results become. Machine learning can also help the algorithms to find and follow rules from statistics and thereby improve and L1 means that time will show how far this technology can come.

The municipality of Alingsås used a powerful computer and they retrained an object detection algorithm using machine learning on their own data. However, the analysis was done on images of a full resolution of 8 cm which meant that the training took 130 hours, and the analysis of the data took 14 days. The data they used were a combination of RGB imaging and relative height data collected with LiDAR sensors by flight. MA1 explains that the challenge with this process is that they have a lot of data and therefor it is also a very time-consuming process. This is expensive to implement, and the method is complex which require a lot of time. However, since its already now is a time-consuming task to manually do mapping from orthophoto, working with this pays off in the long run and it will be worth the effort. As Lantmäteriet, Alingsås also have a few issues with differences between collected data and the data they have collected manually on buildings and use to compare with. Just as for Lantmäteriet one of their issues is the protruded roofs that does not give the buildings the same area as the footprint they have in their system. Despite this the results surpassed their expectations and that they are now in the process of validating the result of their project.

At Lantmäteriet they want to figure out the object recognition first and then move on to change detection. For change detection they have to work with references, either between images from two different times or between data they have and new images. They want to first identify the buildings and then compare the identified buildings over time, and this is something they want to develop methods for. There might also be reasons to change some of their operation to adapt to the data that is collected. One example given was that Lantmäteriet collect information with perspective from above which means the sizes of the buildings are measured in the sizes of the roofs while the data that they compare with are on the foundations of the buildings. This means that most buildings, where roofs are protruded a couple of decimetres there is a difference between the data collected by plane and the data the surveying authority have on buildings. Another challenge the L1 mentioned is to handle shadows and other things that stand in the way when flying and taking images, but this has been trained into the model and they also have strict requirements for flying when it comes to weather and lighting.

According to L1 it is important to use new technologies in the process and to involve the decision makers so that they do not doubt the technology’s possibilities. Furthermore, due to the demanding programs these processes require it takes time to both train the models and to run them. In the future L1 predicts that the administrator who works with this can start the program before they go home and the next day, they have an updated model. This would mean that it does not matter how well staffed they are and how much they can handle but it this gives the opportunity to implement the technique over larger areas and thereby collect more data. Today it is both the data management and the time it takes to fly that limits a wider analysis. Today Lantmäteriet operate with two cameras, but if they would buy more and better ones, they could fly larger areas and more often. They are working towards larger areas with better resolution, but it is a development issue. For Alingsås, when it comes to change detection the MA1 says they are not there yet and that it is a *“long and complicated process.”* Furthermore, they could also have gone even more into detail in the project they have already, and thereby figure out the object level and identify, for example, benches and stone streets.

As Lantmäteriet is an authority, they also have a responsibility towards the society and thus to provide a certain service. According to L1 it is therefore important for them to follow and stay updated on technological developments. The value that change detection and more real time updates bring to the construction industry, is for the end-users. It is the users, such as municipalities, private companies and the general public, who need as current data as possible because it affects the decisions they make. Even other actors, such as police, first responders and military gain value from these updates as they need accurate information to reach certain locations. Both MA1 and L1 highlight that the society should not be afraid of automation taking over people's jobs, because things like this will take time, there will be a change of skills and people retiring and Lantmäteriet's vision is to control the skills towards what is more at the forefront. Both the interviewees agree that implementing AI will give the staff time to focus on other things which they are not able to do today. To spend more time for qualitative work and neglected projects and to develop further digital solutions. MA1 also emphasises that the importance of collaboration and to share their results among each other by saying "w*e will not keep it to ourselves."*

4.3 Results from testing algorithms

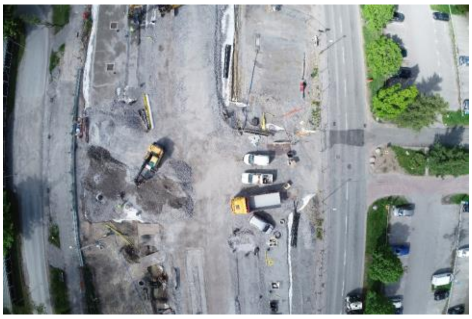
Figure 8: Flowchart of the data processing steps.

Figure 8 shows a flowchart of the process that this chapter follows; Image pre-processing, Change detection and Comparison of methods. This part will show the results of the code testing and other analyses.

4.3.1 Data collection and image pre-processing

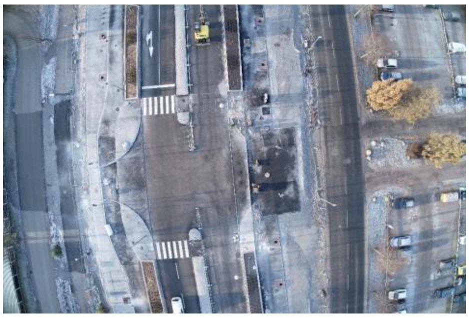
In order for the computers used in this master thesis to be able to process the images, they had to be resized to a smaller size. A choice was made to resize the images to around a fifth of the original size which is consequently the maximum resolution on the images in this part of the thesis. Before starting to process the images and work with feature engineering there is a need to look at the collected data and see what quality the data has and try to identify potential issues that analysing these images may cause.

a) March at 11.30



b) June at 11.00

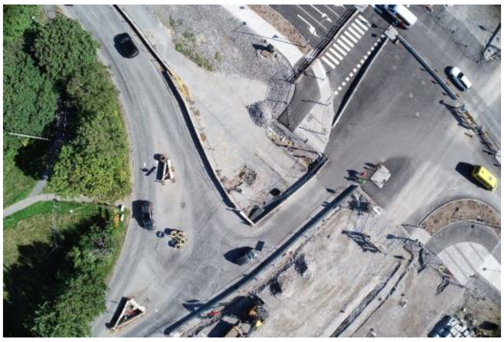
c) October at 11.30



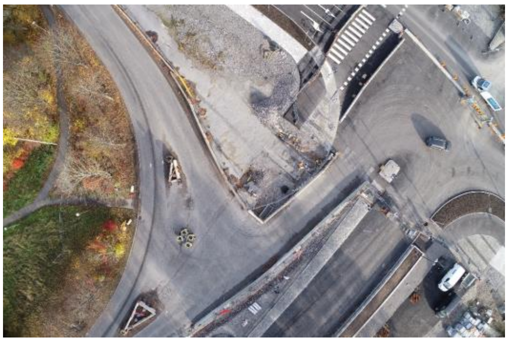
d) December at 11.30

Figure 9(a-d): Images of the same area in an infrastructure project taken at different times.

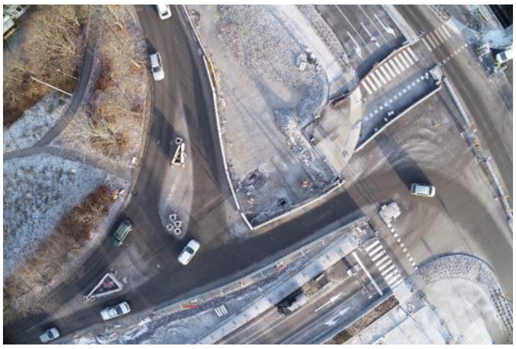
Figure 9a-d show images of the same area of an infrastructure project taken at different times and highlights how much of an area can change between drone flights. Each image is taken at a different time of the year, and on days with different lighting. Despite that the data collection was performed at similar times of the day, for each of them, the shadows and the lights look very different because of the different seasons and weathers. Image 9a and 9b are taken with around three months difference and between those two images a lot of changes has happened. For measuring day to day progress, there is a need for more data of the weeks in between these two. The same goes for all these images. Between image 9a and 9d there are many differences. A change detection test between these two images would most likely give a lot of changes, which would make it hard to follow the progress of the project. Doing change detection between image 9c and 9d could show some relevant and rather easily identifiable changes such as the painting of road lines, however, in image 9d the road is covered in dust which may make the comparison with the newly asphalted road in image 9c slightly harder and may cause errors in the result for some methods.



a) August at 11.00



b) November at 12.30



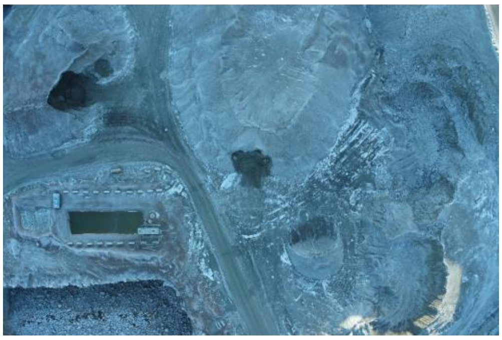
c) December at 11.00

d) June at 12.00

Figure 10(a-d): Images of the same area of an infrastructure project taken at different times.

Figure 10a-d shows that there are many differences between images of the same place that has nothing to do with physical changes such as construction work. Some changes are in weather, season, moving vehicles, lighting, shadows, and the position of the camera and the drone. The last point is especially clear in image 10d where the position is very different compared to the other images. This makes it hard to find any type of result unless the image is retaken, or the position of the drone is more controlled so that these types of errors does not occur. Also, image 10c has a bigger position difference from the two first images. Image 10a, 10b and 10c show the changes in season that can affect the results of a change detection. The different colours might count as changes unless that is addressed and ignored in the results, and trees also have more leaves in the summer which will make the area different also if the colours are accounted for. These issues with the trees are also something that are most likely not interesting to the construction progress but will come up in the result unless that is handled in some way. In image 10c, a difference in weather can be seen as the ground is covered in frost and this makes the grass white and the road darker, which also can result in differences showing up in the results. When it comes to the frequency of data collection the activity going on in these images most likely need less frequent monitoring than the images shown in Figure 9. This is because there are few changes that have happened when comparing the images. the exception being the road between image 10a, 10b and 10c down in the right corner.

a) December at 12.30

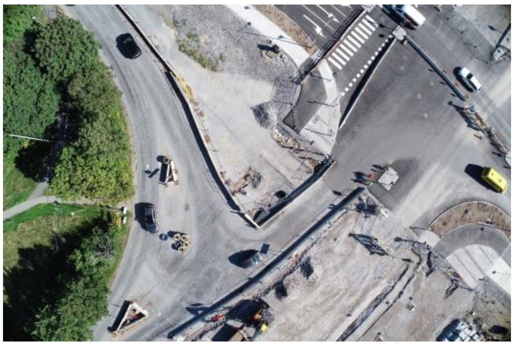


b) October at 09.30

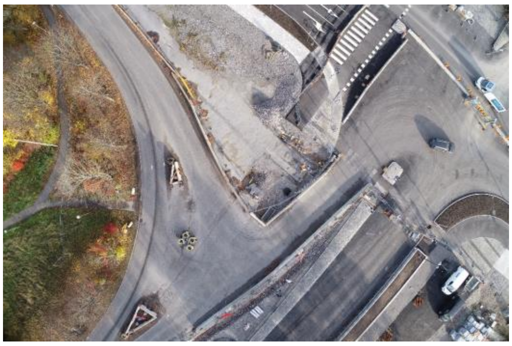
Figure 11: Images taken of the same area of a stone quarry taken at different times.

Figure 11 illustrates how different the light can be between two flights of the same area. These two images are taken in two different months and image 11b was taken three hours earlier in the day than image 11a. In image 11a, most of the quarry is in shadow and the colours are paler and darker. Image 11b has shadows that are more visible and may cause issues when analysed as the shadows are very long and dark compared to the surroundings. In both images there are residue from weather that affects the colour of the ground. Image 11a seems to have some frost that contributes to the pale colour and in image 11b it looks like the ground might be a little wet from recent precipitation which makes the ground darker.

To try and handle the different issues presented earlier in this chapter, there is a need for data pre-processing before the images can be analysed. This is done through feature engineering and are meant to reduce the differences between images and to make them easier to compare. The methods of feature engineering tested in this thesis are black and white, the matching of colours and PCA.



a) Original image 1



b) Original image 2

c) Image 1 in black and white

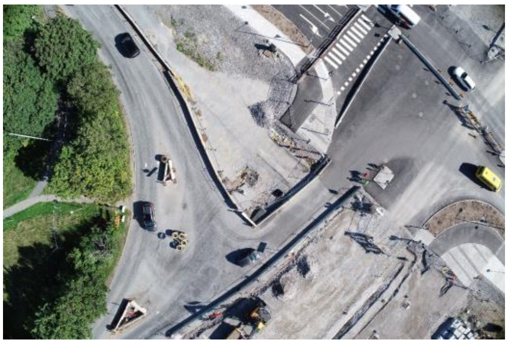
d) Image 2 in black and white

e) Image 1 with matched colours from image 2

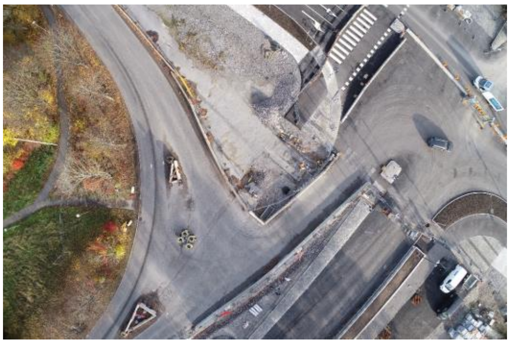
Figure 12: Feature engineering of two images taken of a part of an infrastructure project.

Figure 12 show the feature engineered images and images a and b shows the original images that have clear differences in light conditions and shadows. Image 12c-d shows these images in black and white where it is clear that the images are more similar, at least in colours. However, the shadows are still present. Image 12e show image 12b normalised to the contrast in image 12a. This should hopefully mean that there are fewer differences because of light and colour. The PCA feature engineering method is not presented here as it is part of a model and the result from it is not visual.

4.3.2 Change detection result from testing of algorithms



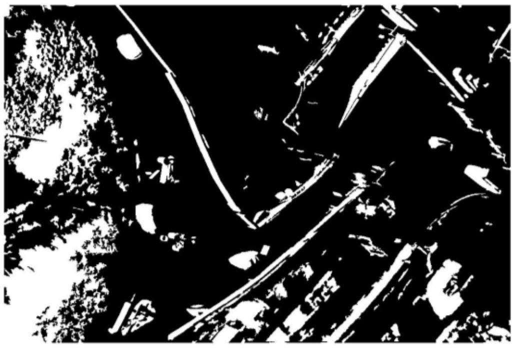
a) August at 11.00



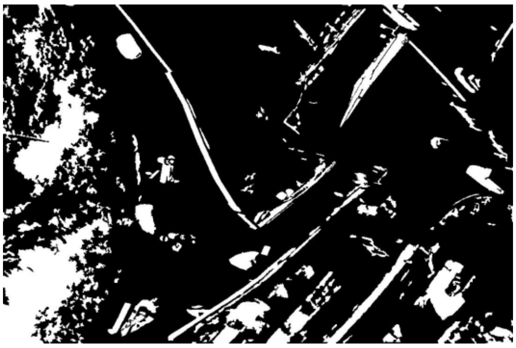
b) November at 12.30

Figure 13: Image from infrastructure project taken at different times.

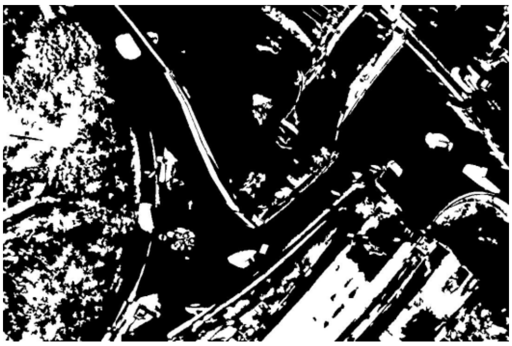
Figure 13 shows the two images that were used in the tests of change detection algorithms. They are used to highlight detections of changes that are less relevant to construction progress such as shadows, cars and colours of vegetation and to see how well the models do detect the activity relevant to construction progress and monitoring. This is done to identify problems that can surface when using change detection methods.



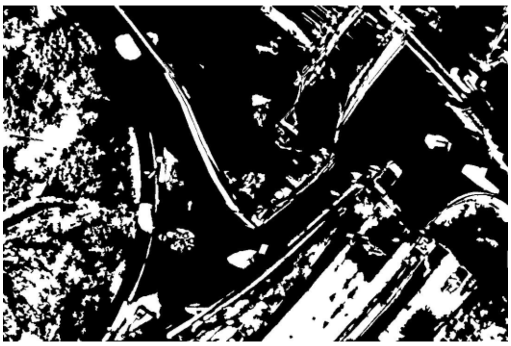
a) Change detection using CWNN



b) CWNN with black and white feature engineering



c) CWNN with colour match feature engineering



d) CWNN with colour match and black and white feature engineering

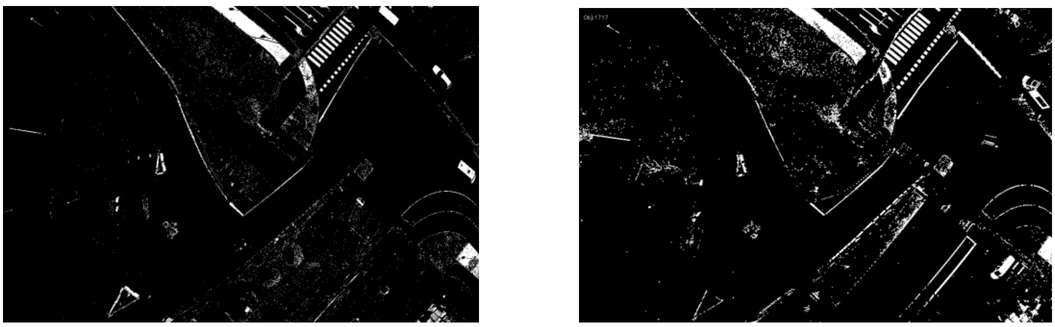
Figure 14: Change detection using CWNN with different feature engineering methods.

Figure 14(a-b) show the change detected using a CWNN algorithm in MATLAB. Image 14a show the result of a change detection using no feature engineering. There are many different types of changes that has been identified but many of the irrelevant to a construction project. The changes in the tress are large and shadows are identified all over the image. The construction work on the road are not completely identified, however, the traffic separators are identified in that their shadows look different in the two images and therefore show up in the results. Image 14b shows the change detected when both images have been made black and white before going through the MATLAB code. This image shows some changes that the coloured images did not and also missed some that the coloured images could identify, but it is very similar to image 14a. Image 14c show the changes detected when image 13a was normalised to the colours in image 13b. Here, there are many differences compared to the other three change detections. This method identifies more details but also excludes a few of the things that is identified in the other images such as parts of the trees. This seems to be the method that can identify most of the change that has happened related to the actual construction progress. The road that is constructed between the two images in Figure 13 and can be seen in the down right corner are the most district change detected in image 14c. Image 14d show the result when the feature engineering methods are combined first matching the colours and then making the images black and white. This result looks quite similar to the method with only matched colours, but it also identifies a few differences that all other methods failed to identify.

a) Change map between the two images *b) Change detection in change map in image a*

Figure 15: Change detection using PCA k-means in Python.

Figure 15a shows the data that is analysed in the Python version of PCA and k-means. Here the algorithm places the two images, that is to be compared, on top of each other and creates the change map shown in the figure to then calculate the differences this image highlights. Figure 15a show the result of change detection using PCA and k-means. This method identifies less of the trees and more of the construction work than CWNN with no feature engineering. Further comparison between the results in Figure 15 and Figure 14 will be analysed in the next chapter.

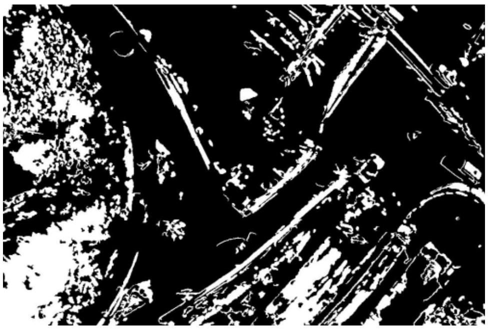


a) Computer vision on image 10a *b) Computer vision on image 10b*

Figure 16(a-b): Computer vision using dilation and thresholds to find contours for image a and b in Figure 13.

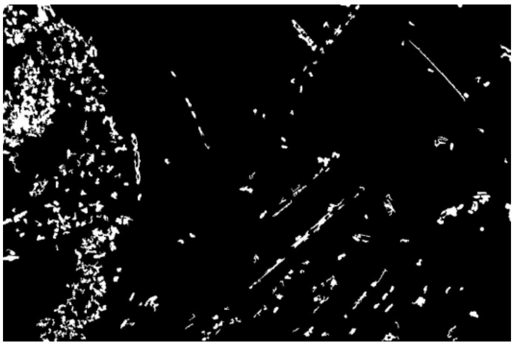
Figure 16 shows the results of a computer vision algorithm that uses dilations and thresholds to find contours used on the images in Figure 13. Here, it can be seen that the algorithm identifies objects with high contrasts such as street paint and traffic dividers but very few contours of objects that are of interest in a change detection model that monitors construction progress.

4.3.3 Compared results

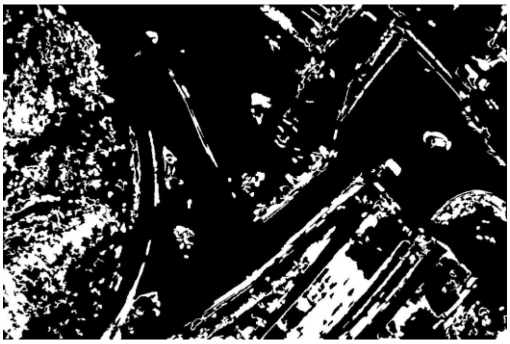


a) PCA compared to no feature engineering

b) Matched colours compared to no feature engineering



c) Black and white compared to no feature engineering



d) Black and white compared to match

Figure 17(a-e): Comparing the results of different methods of analysis and different types of feature engineering.

In this part the results of the tests presented in the previous chapter are compared using the CWNN model in MATLAB. Figure 17 show the results of a comparisons between different codes and feature engineering methods where the black areas are changes or no changes that both methods identified and the white areas are the changes that one model identified and another did not. Image 17a show the difference between the MATLAB code using no feature engineering and the Python code using PCA. Looking back at the images in Figure 14 and Figure 15b it can be observed that the different methods detect different types of changes. The Python code identifies fewer changes in the vegetation but more details in the rest of the differences. Figures 17b and 17c indicate that matching colours make more of a difference than making the images black and white compared to the non-engineered images. At a first glance image 17b and 17d look very similar but looking closely, it can be possible to see that image 17d, where the methods have been combined, is slightly more detailed in its detection of objects than image 17b. Other tests have been performed on the images but none of them gave any valuable results. Some object detection methods were tested but they were not trained on data from the construction industry, and therefore, failed to identify any objects. Other change detection codes could not be analysed due to lack of technical knowledge among the authors, outdated codes and limitations in scope.

5 Discussion

This chapter is a discussion based on the research questions that this thesis investigates. Together with the findings of the literature review, pre-study interviews and image processing results will be analysed. The results of this chapter will be presented in the conclusion chapter.

5.1 How can change detection in drone-captured data be utilised on the construction site?

In the literature multiple examples of other industries that have applied change detection algorithms on remote sensing data have been identified. In the construction industry there are many challenges that might be addressed by using similar technologies. To start, using drones to capture data and then using AI to analyse the changes in that data would according to Elghaish et al. (2021) mean increasing the time managers and workers can spend on other activities. During the interview with both L1and MA1 it became apparent that there are things that today´s way of working with change detection cannot include. Also, A1 was clear about how much time it takes to go thought the data that their drones collect manually. This shows that only using drones do not reduce the workload without using AI to automatically detect changes in the data. The worry that is generally associated with digitalisation, and especially robotics like drones and AI, appears to be less justified in the construction industry than many may think. L1 is not worried that people will have nothing to do, if more automated processes connected to data is introduced, and thereby lose their jobs, but that this development will instead enable them to work with things that are today neglected. Another benefit is that higher automating the monitoring process will require less personnel and can therefor help address the expected labour shortages the sector is facing. The fact that many people in the construction industry today work with collecting information should mean that they in the future can focus more on planning. Furthermore, as change detection should help personnel in making better decision this would help them keep the projects on track with the time plan and economy. Since automatic progress monitoring could also help with catching errors and to follow the project progress, there are double benefits with digitising control processes.

Change detection with the use of AI could offer the construction industry more time to for important tasks and heighten the productivity. It will also give people more control and it may also increase safety for the workers both because they no longer have to walk around on the construction site to do controls and inspections but also because it might be possible to use the drones and the data they collect to monitor dangerous situations and areas. This could work similarly to the drones used for monitoring dangerous areas and detect changes that Said et al. (2021) discuss in mining. Mining is an industry that have many similar activities to the construction industry. Especially when it comes to the type of quarry that the study visit took place at. Here, the industry can learn how to monitor unsafe environments and changes in volumes which might also be applicable on early groundwork in infrastructure and building projects where much of the changes are in the ground structure. The construction sector, similar to mining, has a lot of manual labour and issues with safety. The use mining has had of drones and other technology in reducing the danger for their workers is something that could inspire the construction industry. Drones can move in dangerous and hazardous environments and access remote locations. In the solar energy industry where they use drones and change detection to identify defects on the solar panels, similar technology might help the construction industry to compare the as-built stage with the as-planned BIM model. Many remote sensing cases involve measuring changes in vegetation and structures on the earth. This is the industry that seems to have the most finished algorithms and methods, which means this is another industry from which the construction industry could look for inspiration.

The tested algorithms indicate that it is possible to detect changes in images from the construction industry. However, as the results also show, there are multiple steps that need to be in place, before it can be of much use. As of now, it might be easier to detect changes manually, but as L1 talked about, they have at Lantmäteriet achieved an accuracy that is just as good as the manual detection. This is because they have trained their models of labelled data that fit their operation and can thus increase the accuracy. This means that for construction there is a need to train models and adjust the data collection and data management processes to be able to reach a similar accuracy. Lantmäteriet only looks at a few objects that they can train into models quite easily while the construction industry has much more objects and activities to identify and detect changes. The level of detail for the two types of operations also varies a lot and for construction the level of detail might even vary between objects in the same images, as discussed in Chapter 4.3. There might be a need to combine change detection with computer vision and object detection to get a higher accuracy and to be able to track and monitor different types of objects and changes.

A question that was brought up by both A1 and A2, as well as on the study visit, was the large amounts of information, more specifically Big Data: The many images and other data that the drones collect and that needs to be analysed, processed, distributed and interpreted. There are two aspects of this that can be highlighted. Firstly, the issues of digitally processing large amounts of information and secondly, the problems that too much information can cause for the people who work with it. A1 discuss something that could be called information overload. How much information is too much? There are multiple aspects of this. Too much information can be unnecessary, and there may be a point where more information only causes issues and does not actually contribute with anything positive. Another aspect is the effect these massive amounts of information can have on people. A1 predicted that there might come a point where the amount of information will overcome the commitment of people, and this could lead to that people stop taking in the information and overlook important insights. This can become a stress, and, in the end, this becomes a work environment issue. A construction project has many different roles and all of them require different types of information at different times and frequencies, and with different levels of detail. Also, in many cases, no new insights or information can also be valuable as companies might want to know when nothing has happened as it can mean that they are behind in the time plan. Situations with no new information also needs to be analysed. Another aspect is that too much information can create systems where new data has no changes at all. Therefore, a possibility to handle both too much information, too little information, and also to manage all the tasks used to achieve this, a routine for how to handle this process should be necessary.

5.2 What characteristics of the construction industry can affect an implementation and use of change detection in drone-captured data?

To be able to fully utilise the technology of change detection in data collected by drones there is a need to look at how the industry would handle this type of technology. As the construction sector is unique in many ways, that means that technologies from other industries might need to be adjusted and adapted for it to work in construction. Projects with many involved stakeholders, something that construction is notorious for, can cause digital initiatives to become complicated. The literature explains that the construction industry is fragmented and project-based, and that there are needs in the construction sector that other industries do not have. This affects how possible it is to transfer learnings from other industries and how to collaborate with actors that also work towards other industries. The dynamic projects that the construction industry is characterised by also put a high demand on sufficient progress monitoring. When most projects are unique it is, in this process, hard to share knowledge on digital developments between projects. As the interviewees emphasised, as of now there is a lack of knowledge and competence within the field of AI, and thus machine learning, in the construction industry. Ribeirinho et al. (2020) even says that the knowledge level is especially low in construction which could indicate that construction need to work extra hard to develop digitally. In the interview with L1 there was some expectations that this will start to change as a new generation of people start in the industry and bring new ideas and knowledge.

Both the interviews and the literature, bring up the importance of collaboration when it comes to implement digital tools. Many stakeholders involved in projects can cause disruptions to digitalising initiatives as everyone might not have the will or ability to use the technology. Some of the smaller companies might also have a hard time joining in investments due to their low economy of scale. The fragmented industry will most likely require larger companies to take the lead but also require a will from all types of companies to work together. To collect and process images, as have been studied in this thesis, might be something one company can do but the result is something that many actors hopefully will have use of. However, to fully utilise this they must know what they want, and they have to communicate that as well as understand the results. There is also the need for financing the digital investments in projects but here, as the study visit brought up, there are needs for proof of concepts. To show people what they will gain from using drones and AI for progress monitoring and also, to show the people in charge that it is worth investing in things like drones and digitised progress monitoring. Even if there has been little research about this subject within change detection, the interest in AI have increased over the years, and thereby, it should not take long time before the construction industry start to realis the overall benefit of automatic detection. Other industries have shown that using technologies such as drones and AI have increased their productivity, and this should mean that the same would happen for construction as well.

As mentioned earlier, the results from Chapter 4.3 show that it is possible to identify changes. The issue is that not all changes are relevant or even changes at all but just interference in the images. Even if the flight is done at appropriate times and there are attempts to try to reduce the differences in the captured data, there will still be interference that cannot be avoided. This means that there will be need to manage the collected data further through pre-processing and feature engineering. However, as the results of the tests show, even with feature engineering the algorithms still catch irrelevant differences, such as differences in lighting, seasons and shadows. When collecting data there are many aspects to consider. Decisions have to be made on what drones to use and what type of sensors that are the most suitable for a construction site. The test that the results present are done on high resolution images captured by an RGB camera mounted on a multi-rotor drone, however, there might be necessary to use other cameras and to combine methods of data collection. The municipality of Alingsås, for example, combine their images with height data collected using laser and thereby they achieve a higher accuracy.

Another aspect is the monitoring frequency. Different types of projects will need data collection at different intervals. As the results show, these frequencies can vary a lot and they might be different from other industries. Another important aspect that the study visit brought up is the fact that different people and roles in a project need different type of data and information at different times. Some might want a lot of data while other might only see the long-term change as interesting for them. This also differs from project to project. In some cases, it might not be relevant to fly with the drone more than once a month and in others it might be necessary to fly as much as once a day or even more. For the images tested in this thesis the frequency is around one month and for some changes this is just enough while for others a higher frequency of data collection is needed. For the construction progress seen in Figure 10 in Chapter 4.3, there might not be need for a higher frequency, but for monitoring safety equipment, such as temporary traffic dividers and signs, in the same images there are need for more frequency. This because, as can be seen in all four images in the figure, the temporary object with four circular objects functioning as an intersection, change positions between every image. Other industries use satellites more and more since these are beginning to get a relatively high frequency of measurements for up to a week. For construction this is might not be enough. The level of detail needed might also be too high for satellites to catch.

With frequency the issue of weather and shadows become an issue. As the theory and interviews highlight, it is not possible to fly with the drones during bad weather. This can make it hard to fly at the desired frequency which could interrupt the monitoring process. Also, if the desired frequency requires flights at different times of the day and over seasons the lighting becomes an issue. The data then contains different types of light conditions and have shadows in different directions and of different lengths which becomes clear in the images in Chapter 4.3. This then affects how well the images can be processed. If the data collections happen very close together, for example, every hour, the differences in season and light should become less relevant. However, if this frequency is not necessary it will not be worth the lack of interference as the data collection is unnecessary and the results will be few or none at all. Moreover, when discussing the weather and seasons, if the industry wants to monitor progress all year the issues with snow, rain and light conditions need to be dealt with. To monitor projects in the winter in areas that get snow there will be need to complement the images with other sensor data that can measure through the snow. As mentioned previously, there are many types of interference in images and to manage these issues and get more accurate results there might be need to add LiDAR or similar sensors that handle these types of interferences differently. The need for feature engineering is universal for most industries but the high frequency that construction need might increase the importance as they are going to want to measure in situations where the conditions will not be ideal.

The construction industry deals with thousands of different unique objects that all need to be trained into a model that would detect them. Today, as Bognot et al. (2018) and Nath & Behzadan (2020) mentioned, there are very few datasets that can be used on construction and those that do exist are small and are not enough to accurately train large models on. On the study visit, the need for a common national data base was brought up and (S. Xu et al., 2021) also mean that there is a need to create extensive datasets that contains labelled images and objects from the construction industry. Other industries have worked forward datasets for training their models over some time and there are now algorithms that work on detection objects specific to those industries. This cannot completely be applied to the construction sector that have different, and sometimes unique, objects and have need for high level of details that some other sectors do not. Companies and other actors should come together and create national or international repositories for objects and images that can be used to train models for change detection, object detection and more. MA1 explained that labelling data and training models are an expensive and time-consuming process but that it can be worth it in the end. However, as most current models are trained on land changes the models have to be retrained with data from the construction industry. The problem with lack of datasets in this case would make the construction industry a candidate for transfer learning. To take algorithms and models from other industries, as remote sensing and agriculture, that have well trained models and retrain them on data from construction. This will still require larger sets of data than are available today but not as many as would be required when training from scratch.

Other barriers for implementing change detection and drones are the laws and regulations that monitor air space and data collection. There are restrictions on how to fly, which in the interviews were brought up as barriers for further development due to the limits on where they can fly and requirements on a pilot to be present. If they want to fly more extensively and more frequently there are laws that will put restrictions for such a development unless they are adjusted. Also, the data protection regulations might make it harder to collect different types of data. However, this is an ethical issue that are meant to protect people's integrity and this issue will have to be carefully considered when working with drone-captured data. Other important things to consider is the sustainability implications of using these technologies. Digitalisation in general usually decrease the environmental impact of processes, however, digitalisation might also increase the frequency of certain activities, for example flying with drones more often than manual monitoring is done, which could increase the emissions that are created.

5.3 Sources of error

Reflecting on this thesis there are a few things to highlight. The limited knowledge that the authors of this thesis had in the area of AI and technology have limited the possibilities to do deep analyses on technical solutions and issues which is a reason to why this was left out of the scope. The limited access to processing power was also an issue and this led to the need of reducing the sizes of the images. This will have affected the result as data was removed. The few available datasets and lack of labelled data also made it difficult to try models that required this which means that the area of object detection in monitoring of change has not been properly addressed. Along with this, there are sources of errors, such as; unreliable image position, potential error in collected data and potential error in code. Furthermore, the data used in this thesis only came from one company which can mean that there is bias in the data that might make application of the result on other companies harder. Since this is a relatively new field, especially in the construction, there was a lack of studies on the specific topic of automated change detection using drones. This mean that the results are speculative and in need of further data.

6 Conclusion and further research

This master thesis has investigated how AI and change detection can be used on drone-captured data to help automate construction progress monitoring. There seem to be a potential to replace certain manual tasks with automatic change detection. The results of this thesis indicate, based on tests and research on how other construction and industries are working, that this method can be used to create benefits that the construction sector can gain from. This thesis has looked at how change detection in drone-captured data can be utilised in the construction industry and how the characteristics of the industry can affect attempts at implementing and using this technology. The hope is that this will help the industry in taking the first steps towards automating their progress monitoring processes and addressing the challenges that the construction sector is facing.

- *RQ1: How can change detection in drone-captured data be utilised on the construction site?*

Change detection can have many uses on a construction site, especially in progress monitoring. Tracking changes and errors almost in real time can help keeping time-plans and budgets. Identifying errors or delays early can assist managers into making better decisions which would reduce time and budget overruns in projects, thereby helping the industry to become more productive. When drones perform the data collection this will also relieve personnel from time-consuming tasks as inspections. This would mean that workers can spend more time on other tasks that might have been neglected and this could also help meet the labour shortages that the industry is facing. Another utilisation area is the reduction of the need for personnel to walk around the construction site to do manual monitoring thereby reducing the risk for accidents. When drones collect data, they can move in hazardous environments regardless of ground conditions. The collected data can then also be used to track safety related equipment and monitoring structures that could cause harm.

- *RQ2: What characteristics of the construction industry can affect an implementation and use of change detection in drone-captured data?*

The construction industry is unique in many areas, and this affect how the industry can use and adapt work methods from other industries. Most companies in construction projects are small and do not have the economy or the skills to participate in digital development projects unless larger companies take initiative. There is a lack of national datasets and libraries that can be used to train models specific to the construction sector that is an industry with many unique objects. The large range in types of objects and the large amount of data that needs to be monitored may also motivate for combining methods of change detection with object detection to more easily monitor activities. Another aspect where construction differ from other industries is the requirement on frequency of measurement to be able to accurately follow the progress. Moreover, Big Data is a concern as the construction sector has a lot of information, and this may cause problems for computer systems and cause stress among the people handling the results. Furthermore, there is a need to discuss and understand the impact laws have on this process and to investigate the ethical implications such a system would have. It is also important to identify possible negative and positive effects this could have on sustainability.

In order to effectively use change detection and AI to monitor progress with the help of drones in construction there is a need to plan the process. To test and make decisions on frequency, data management as well as collection methods. Furthermore, routines for data storage and distribution should be discussed along with assessments on what roles needs what types of information.

6.1 Further research

As this is an explorative study, there are many areas of further research that can be investigated. For example, a next step can be to work on frameworks for creating datasets in construction or to explore and test the technical aspects of change detection and how it could work in a project process. There should also be more extensive case studies done on successful implementations and perhaps also comparisons between cases in other industries and construction projects, including transfer knowledge between industries. As a next step in construction management there should be studies that follow projects all through the different stages identifying the types of changes and objects that can be of interest to detect. This could then be used as a base for what methods to use when creating models to implement in the industry. There should also be studies that create models and algorithms specifically for the construction industry and when these models have been created there should also be studies on different cases to assess the accuracy. Furthermore, studies on how to increase the knowledge on AI and drones in the industry, to look at how collaboration can be used to catalyse digital initiatives, and to explore how to manage changes that digitalisation will have on the construction sector, would be of great value.

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8 Appendix A: Resizing of images

Appendix A1:

```python
# Resizing for Python

import cv2
import numpy as np
import os

image_path = (r'filepath\imageName.jpg')
out_dir = (r'filepath\output')

# Read image
image = cv2.imread(image_path)

# Check size
print(image.shape)

# Resize image
new_size = np.asarray(image.shape) /5/5
new_size = new_size.astype(int)*5
image = cv2.resize(image, (new_size[1],new_size[0])).astype(int)

# Check size
print(image.shape)

# Saving image
cv2.imwrite(os.path.join(out_dir, 'image_out.jpg'), image)
```

Appendix A2:

```
# Resizing for MATLAB

import cv2
import numpy as np
import os

image_path = (r'filepath\imageName.jpg')
out_dir = (r'filepath\output')

# Read image
image = cv2.imread(image_path)

# Check size
print(image.shape)

# Resize image
new_size = np.asarray(image.shape) /5/5
new_size = new_size.astype(int)*5-4
image = cv2.resize(image, (new_size[1],new_size[0])).astype(int)

# Check size
print(image.shape)

# Saving image
cv2.imwrite(os.path.join(out_dir, 'image_out.jpg'), image)
```

9 Appendix B: Feature engineering models

Appendix B1:

```python
# Making images black and white

import cv2
import os

image_path1 = (r'filepath\imageName1.jpg')
image_path2 = (r'filepath\imageName2.jpg')
out_dir = (r'filepath\output')

# Reading images in black and white
image1 = cv2.imread(image_path1,0)
image2 = cv2.imread(image_path2,0)

# Saving images
cv2.imwrite(os.path.join(out_dir, 'image_ouput1.jpg'), image1)
cv2.imwrite(os.path.join(out_dir, 'image_ouput2.jpg'), image2)


```

Appendix B2:

```python
# Matching the colours in the images

import cv2
from skimage.io import imread, imsave
from skimage import exposure
from skimage import color
from skimage.exposure import match_histograms

image1_path = (r'filepath\imageName1.jpg')
image2_path = (r'filepath\imageName2.jpg')
out_dir = (r'filepath\output')

image1 = cv2.imread(image1_path)
image2 = cv2.imread(image2_path)

matched = match_histograms(image1, image2, multichannel=True)

cv2.imwrite(os.path.join(out_dir, 'image_out.jpg'), matched)
cv2.imwrite(os.path.join(out_dir, 'image_out2.jpg'), image2)


```

Appendix B3:

```
# Making images black and white and then matching the colours in the images

import cv2
from skimage.io import imread, imsave
from skimage import exposure
from skimage import color
from skimage.exposure import match_histograms

image1_path = (r'filepath\imageName1.jpg')
image2_path = (r'filepath\imageName2.jpg')
out_dir = (r'filepath\output')

image1 = cv2.imread(image1_path)
image2 = cv2.imread(image2_path)

matched = match_histograms(image1, image2, multichannel=True)

image1 = cv2.cvtColor(matched, cv2.COLOR_BGR2GRAY)
image2 = cv2.cvtColor(image2, cv2.COLOR_BGR2GRAY)

cv2.imwrite(os.path.join(out_dir, 'image_out1.jpg'), image1)
cv2.imwrite(os.path.join(out_dir, 'image_out2.jpg'), image2)
```

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