University of Nevada, Reno

Improving Highwall Monitoring Through Fracture Identification in Open-Pit Mines Using Image Segmentation

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Mining Engineering

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ABSTRACT

Open pit highwall monitoring is an important part of maintaining safe mine operations. The current monitoring practices are ideal for tracking mass slope movements through round-the-clock monitoring of ground acceleration, but they are not well suited for quantifying the extent of damage to the highwall by mining practices like blasting or in-situ conditions like faults and joints, which can lead to rockfall events that can harm people, damage equipment, and halt operations. The current monitoring practice to account for this gap is through in-person inspections by geotechnical engineers, which leaves the potential for large areas of the open pit highwall to go without coverage since there is only so much a human can do. There is current research focusing more on locating areas along the highwall where rockfall might have already happened, for example, using multispectral imaging, but the fracture prevalence has very few researchers looking into it. For this study, researchers utilized a U-Net model for image segmentation to identify cracks and fractures along the open pit mine highwall, aiming to enhance the current monitoring technique of visual inspections employed by geotechnical engineers. Unmanned aerial vehicles were used for data collection as they could access more of the highwall and capture high-quality imagery. Image annotation to label the cracks and fractures in the images was performed, developing the dataset needed to train a deep learning model such as U-Net. Several training schemes were followed to account for low amounts of data and to see which configuration would produce a good model for the problem at hand. Traditional edge detection using the canny edge detector was also used to illustrate the differences in prediction and workflow between deep learning methods and more traditional detection methods, such as edge detection. The model trained with a mix of original and augmented images gave the best performance at 97% accuracy and a relatively high intersection over union (IoU), as well as producing segmentations close to the GroundTruth segmentation mask.

DEDICATION

I dedicate my thesis work to my parents, Motsisi John Letshwiti and Boikaego Binah Letshwiti, and my siblings, Tshepo Letshwiti, Tlhompho Letshwiti, and Thabang Letshwiti. I would not have made it as far as I have without their support throughout the years.

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TABLE OF CONTENTS

TABLE OF TABLES

TABLE OF FIGURES

CHAPTER 1 : **INTRODUCTION**

Mining has been a thriving industry for many years. Throughout that time, the industry has undergone many transformations as new technologies emerge. Some of the transformations were aimed at improving safety, ore recovery, mineral recovery, and reducing costs. One of the biggest innovations to date has been the use of explosives. In large-scale mining, the most energy-consuming part of the process is rock breakage. To move the rock containing the ore through its beneficiation process, it needs to be progressively broken down into smaller chunks that can be handled by each stage of the process. Using explosives to break down the rock at the very beginning of the mining process has proven to be the most energy-efficient way to do it.

However, the benefit of using explosives for rock breakage comes with certain downsides that the mining industry is always attempting to minimize. These negative impacts will usually couple themselves with other rock conditions that are inherent in that rock structure, which may lead to poor ground conditions in mining highwalls, resulting in rock falls and highwall stability issues. As the demand for resources grows and thus the need for more mining grows with it, issues like rock fall may also become all too common, resulting in greater challenges in the area of mine safety and efficiency. With that said, it is imperative that researchers in the mining industry attempt to address some of these current and pending challenges using modern technologies such as Artificial Intelligence (AI) and hardware such as unmanned aerial systems (UAS) and autonomous equipment. This thesis work will look to add to some of the work that has already been done here at the University of Nevada, Reno to improve highwall and rockfall monitoring to foster safety and productivity in the industry.

1.1 BACKGROUND

Mining is an industry concerned with the extraction of minerals from the ground (Hartman, 2002). It is made up of four-unit operations that must be executed successfully: drilling, blasting, loading, and hauling. Drilling is the mechanical creation of a small diameter hole in the rock mass. It is done mainly for the adequate placement of explosives that will deliver the needed fragmentation energy (Darling, 2023). Blasting follows drilling, it is the release of energy from explosive compounds, which then fragment the rock around it. Loading and hauling involves the transportation of the blasted material from its current location in the pit to some destination, such as the processing plant or waste dumps.

The drilling and blasting processes have the most impact on the downstream processes and on the safety conditions in the open pit in relation to rockfall occurrences and the highwall condition. These impacts will be discussed further in later chapters, but it is clear that as the demands on the mining industry grow, there is more need for advanced monitoring techniques that will assist engineers by providing more data for better decision-making and an overall safer working environment.

1.2 PROBLEM STATEMENT

Securing the highwalls of a pit is an extremely important activity in any mining operation. The current practices of monitoring mining highwalls rely on geomechanical techniques that are mostly concerned with the movement of large areas of the highwall slopes over time and less so on rockfalls that may be lurking. Currently, there are no methods that monitor the structural appearance of the highwalls to supplement the visual inspections conducted by engineers in their day-to-day tasks. However, with the uncertainty under which mining operates, it is imperative to collect as many data points about the mining environment as possible.

With the emergence of new technologies like Unmanned Aerial Vehicles (UAVs) and Machine Learning (ML), new capabilities are being realized in the mining industry. (Ali & Frimpong, 2020) documents the many ways in which emerging technologies are being used and can be used in the mining industry now and in the future. UAVs or drones with different kinds of sensors are being deployed to collect data in different ways, which opens up new avenues of analysis to be pursued (Bamford et al., 2020). Images collected from drones give a new perspective to engineers about the mining environment, and those engineers can use that information to gain new insights about highwall conditions, pit and road conditions, working bench conditions, tailings ponds, and the mine site as a whole. With these new developments, interesting areas of research are also emerging. This thesis work is part of a larger project that was aimed at applying artificially intelligent systems to mining, with the aim to improving safety and productivity. It will look at presenting a new approach to determining the condition of the highwall in lieu of visual inspections by personnel during daily operations. The current practices only consider compliance with the mine designs and if there is movement of rock on the highwall in terms of accelerations that may lead to failures. But there is no work done on documenting the condition of the highwall, mainly if any fractures can be observed on the remaining highwall which may possibly lead to instantaneous events like rockfall.

1.3 RESEARCH QUESTIONS AND OBJECTIVES

The aim of this thesis work is to examine the conditions of the remaining highwall in an open pit mine using computer vision methods as a way to offer more insight into the mining environment from the data that is being collected. This thesis looks to show how modern technology like drones and machine learning can be used to further the understanding of the mining environment and how that can give engineers a new perspective and improve safety conditions. In order to do this, the following research question must be addressed:

1. What are the possible causes of cracks and fractures on open-pit highwalls? and how do they affect highwall stability?
2. Can unmanned aerial vehicles (UAVs) imaging and deep learning be used to detect major and minor cracks on mine highwalls?

1.4 SCOPE

The work that will come from this thesis project will have the potential to be used for a wide range of areas in the mining industry as a whole. Still, due to limited data for this thesis work, the scope will be limited to demonstrating the value of this work from data originating from mine operations in the Reno area and some operations in Arizona. Due to this, special consideration may be given during this work to mining practices and geological conditions found in this area, which may not be applicable elsewhere.

With that in mind, the following areas will be explored:

- Reviewing of literature on rockfall, highwall stability, and factors such as rock mass properties and blasting practices that affect it.

- Review literature on machine learning, and computer vision, how they are used in the mining industry, and how it applies to this work.
- Review literature on the use of drones as an imaging technique in the mining industry.
- Data collection and image processing.
- Pre-process images for machine learning or deep learning algorithms.
- Train a machine learning deep learning model on highwall images to detect fractures.

1.5 REPORT OUTLINE

This section will complete the introduction chapter and give an overview of what to expect in the rest of this thesis document. Chapter 2 consists of literature review on open pit mining methods, highwall stability, factors that affect it, machine learning, image processing, and computer vision. It will also provide information on the use of drone technology and photogrammetry in collecting data at mining operations. It will give the reader a chance to get familiar with some of the topics that will be discussed in later chapters and also provide valid reasoning for the necessity of the work. Chapter 3 will dive into how data was collected, the drone technology used, the software used for data collection and processing, and the site locations that were appropriate. The methodology followed to pre-process the images collected, and the machine learning models coded to train and make predictions will be discussed in Chapter 4. The results and performance of the models, together with important discussion points will also be in Chapter 4. Chapter 5 will close off the document with the conclusion and any future work that can be pursued.

CHAPTER 2 : LITERATURE REVIEW

This chapter will look at the literature that is available and relevant to the topics that will come up in this thesis work. Open pit mining methods will be looked at, and how highwalls are formed and managed in that setting. Drill and blasting practices, highwall monitoring, and other relevant monitoring techniques will be considered. The use of drones in modern survey methods and how they give mine operations a new perspective on their mine environment will be discussed. The fundamentals of Artificial Intelligence and Machine Learning will be discussed. The impact that these new technologies have on mine operations in the areas of geomechanical, drilling and blasting, and the monitoring techniques that come with them.

2.1 OPEN-PIT MINING PRACTICES

Selecting a mining method is an important part of the mine feasibility study. Open-pit mining as one possible mining method, is the extraction of valuable ore by accessing it on the surface of the earth. The orebody is mined from the top down in a series of horizontal layers of uniform thickness called benches (Sjöberg, 1996). As each bench is mined to exhaustion, a vertical cut called the bench face is left behind. The combination of all these bench faces as the orebody is mined to the bottom elevation makes up the highwall of the open pit. The bench face and the highwall both have to be sloped at certain angles to maintain the structural integrity of the open pit.

These slope angles are determined by geomechanical engineers based on several data points collected in the area. Rock mass properties, structural geology features such as faults and shear zones (Osasan & Afeni, 2010), groundwater content, alterations in the orebodies, and other in-situ rock stresses. All of these points of interest in the area to be mined are then incorporated into the open pit designs or mine plans by mining engineers. As mentioned above, the structural integrity of the open pit, which is achieved through the stability of the highwall, is of great importance, and the subsequent mining processes of drilling, blasting, loading, and hauling have to be in line with the design parameters.

2.2 DRILLING AND BLASTING

Drilling is the first step in the mining process. It is the creation of a small diameter hole in the area of interest, in which explosives are placed. Drilling is done mainly for the placement of explosive material in order to deliver fragmentation energy precisely where it is needed (Darling, 2023). There are a number of considerations to account for when creating a drilling plan, and most have to do with the rock mass properties, geologic structures, and the economics of it all. The rock mass properties will dictate the drillability of the rock. Drillability of rock means the actual or projected rate of penetration in a given rock. It is a combination of several factors related to rock properties such as density, compressive strength, tensile strength, hardness, toughness, brittleness, coefficient of internal friction, and abrasiveness (Nunoo et al., 2016). Drillability will affect the types of drilling equipment used to achieve the depth of drillholes, the diameter of drillholes, and the time frame in which to achieve this.

After drilling, blasting is the next stage. Blasting is a chemical, physical, and mechanical process that involves the initiation of explosives for the purpose of breaking in-situ or large rocks into smaller rocks in a mining or construction setting (Girard & McHugh, 2000) and the demolition of buildings in the construction industry. Explosive material deposited in a blast will generate a high volume of gases and a huge amount of heat within a short period of time in a confined space (blasthole). This results in a high-pressure environment in the blasthole, which is exerted on the surrounding rock (Nunoo et al., 2016). The combination of high pressure, confinement, and heat will lead to the development of cracks and rock breakage.

Drilling and blasting (D&B) has one main goal, which is to generate broken rock at the fragmentation needed for downstream mining processes such as loading and hauling, comminution (crushing and grinding), and mineral concentration processes like flotation. In pursuit of this fragmentation, other outcomes are also considered in order to ensure future operations are not impacted. Before D&B operations begin, a mine plan is drawn up that will be followed to ensure that the right material, through the proper sequencing, is drilled, blasted, and hauled to downstream processes. Thus, apart from reaching the desired fragmentation, achieving the drawn-out mine plan is an important goal. Drilling and blasting has other outcomes apart from fragmentation, that affect how a drilling and blasting operation is conducted. These outcomes will usually have an impact on the ground conditions around the pit, so it is important to know about them and control for them in the D&B process. These outcomes will be discussed in more detail in later sections.

2.3 LOADING AND HAULING

Following drilling and blasting is the load and haul process. This is another unit operation in mining (Hartman & Mutmansky, 2002) that involves the transportation of blasted material, ore or waste, from the mining area to the process plant or to waste dumps. In large scale open pit operations, the most common equipment used in load and haul operations is the shovel and haul trucks. Shovels are the typical loading units (Darling, 2023), they scoop up the blasted material from the ground and load it into haul trucks, which will then transport that material to another destination, usually outside the open pit. Just as is the case with blasting, loading and hauling also play a role in the condition of the highwall during mining, but their role is a secondary impact born from the outcomes of drilling and blasting. These will be discussed in more detail in the section below.

2.4 IMPACTS OF UNIT MINING OPERATIONS ON HIGHWALL CONDITIONS

As mentioned above, the unit operations of drilling and blasting, loading and hauling have some impact on the mine highwall. To understand how these unit operations may affect the highwall condition, it's important to understand the in-situ conditions before mining operations begin. Prior to the start of mining, exploration is carried out to determine the condition of the ground on which mining will occur. The information gained from this will be used to inform many activities, including the type of drilling and blasting that is done to fragment the rock. However, due to the diverse nature of rock mass properties, it is hard to precisely determine what the outcome of any drill and blast plan will be and how it will affect the remaining highwall.

Backbreak is one of the major outcomes of D&B, it refers to the excess breakage of rock induced by blasting past a certain limit, which is usually the last row of drillholes (S. Kumar et al., 2022). When a section of highwall experiences a significant amount of backbreak, it weakens the area, leading to over mining of the area by the shovels or loose material primed to result in a rockfall event. Backbreak can occur as a result of poor blast planning from an engineering standpoint or due to the presence of excessive geologic structures in the ground. Geologic structures are features and arrangements within Earth's crust that result from the deformation and movement of rocks over geological time, these include faults, folds, joints, and shear zones, just to name a few. Blast induces ground vibrations throughout the surrounding rock, and this may also lead to fractures and loose rocks along the highwall. Table 1 below outlines some of the damage that can be observed at different levels on the bench highwall after blasting.

Table 1 Levels of damage to pit walls produced by blasting(Carlos et al., 1987)

Arbitrary damage level	Observed conditions of the wall		
	Joints & blocks	Dip angle appearance and conditions of face	Digging condition at face
1. Slight		>75°	
	Joints closed, infilling still welded	If used, semi-circular sections of wall control holes seen	Scars of shovel teeth seem in softer formation, further digging not practical
2. Moderate		>65°	
	Weak joint infilling is broken, occasional blocks and joints slightly displaced	Face is smooth, some hole sections seen. Mine cracks	Some free digging possible, but teeth 'chatter'
3. Heavy		>65°	
	Some joints dislocated and displaced	Minor spalls from face. Radial cracking seen	free digging possible >5ft with some effort
4. Severe		>55°	
	Face shattered, joints dislocated. Some blocks disoriented	Face irregular, some spalls, some backbreak cracks	free digging possible <10ft
5. Extreme		55°>37°	
	Blocks dislocated and disoriented, blast-induced fines observed	Face highly irregular, heavy spalling from face, large backbreak cracks	Extensive free digging possible >10ft

From the Table 1 above, it is evident that a pit highwall can experience different degrees of damage from blasting, and the structural geology features present in that area of the blast will affect the extent of the blasting and excavation impact. Because of the damage that the highwall can endure from basic mining operations, monitoring these highwalls is an important part of the safety processes in open pit mining. This is part of the motivation for this thesis work, it will help engineers better determine, in a more efficient way, the level to which the highwall may be damaged and thus tailor operations in that area to compensate for that. The next section will get into the current monitoring methods being used in the industry.

2.5 GEOMECHANICAL MONITORING

In open pit mining, the area of geomechanical engineering is of great importance to the safety of people and equipment, and to ensuring that future operations in the area of the pit are not impacted by current actions. To be able to achieve these objectives, monitoring, which is a significant part of the geomechanical team in mining, has to be conducted at all times. (Sjöberg, 1996) indicates that the hallmark of a good monitoring system should focus on maintaining safe operational practices, providing advanced notice of instabilities, and providing additional geotechnical information regarding slope behavior in the open pit. Slope monitoring techniques can be categorized in different ways, (Sjöberg, 1996) indicates that there are two such categories, namely surface and subsurface measurements. However, a more recent publication (Osasan & Afeni, 2010) shows that there can actually be three categories to group the monitoring techniques, these are visual inspections, surface/subsurface measurements, and remote monitoring. This goes to show that as new technologies come on board, new and improved methods of operations will be discovered.

2.5.1 SURFACE MEASUREMENTS

Surface measurements in geomechanical and geotechnical settings involve some techniques and equipment placed on the earth's surface, be it on highwalls, benches, or haul roads. These equipment and techniques are mainly for the measurement of rock slope geometry and rock movement that may be occurring undetected. Survey Network, tension crack mapping, surface wire extensometers (Osasan & Afeni, 2010; Sjöberg, 1996), and the equipment used includes total stations, prisms, radar, laser scanners, terrestrial lidar, and wireline extensometers (Nunoo et al., 2016).

A survey network refers to a combination of target prisms strategically placed around the pit highwalls in and around areas where instabilities can be expected, and one or several non-moving control points for the survey stations (Girard & McHugh, 2000). The way the system works is that angles and distances between the survey station and the target prisms are measured periodically to establish a record of the movement of the slopes or highwall. Drastic changes in movement of the different slopes in the pit can then be noted as they occur, and warnings can go out as promptly as possible.

Tension crack mapping is another important practice in slope monitoring. Tension cracks usually occur at the crest of slopes or highwalls, and they indicate that the tensile stress in that area exceeds the tensile strength of the rock. Changes in crack width and direction have to be monitored and measured to determine crack propagation and establish the extent of the unstable area (Girard & McHugh, 2000; Osasan & Afeni, 2010). Wire extensometers are also another informative way of monitoring slopes. They are instruments that monitor the deformation or displacement of rock under various loads or conditions (*Extensometers*, 2023). The portable wireline extensometer is a common method of measuring movement across tension cracks. The usual setup is made up of a wire anchored on the unstable side of the ground, and a monitor and pulley station located on the stable side, behind the tension crack (Girard & McHugh, 2000). As the unstable ground moves away from the pulley system, the displacement on the wire can be recorded.

There are a number of other methods that are being employed for surface measurements, and they rely heavily on new technology coming into the market. These include radar monitoring devices such as slope stability radar (SSR), terrestrial laser scanning (N. Q. Long et al., 2018), and InSAR systems that continuously scan and compare high-resolution measurements of slope face for any movement, no matter how small (Nunoo et al., 2016).

2.5.2 SUBSURFACE MEASUREMENTS

These types of measurements are usually gathered with equipment placed below the surface of the ground, sometimes in boreholes, to gather data on water content, pressure, and any subsurface rock movement that may be occurring. The equipment that is used includes piezometers, inclinometers, and borehole extensometers.

Piezometers are a class of instruments used for measuring groundwater pressure and water levels (Darling, 2023). The stability of highwalls can be negatively affected by the presence of groundwater. Water pressure can reduce the shear strength of failure surfaces and increase forces that induce sliding in tension cracks. Freeze-thaw cycles can increase the weathering of rock, which may lead to further instability (Wyllie & Mah, 2017). Piezometers will specifically measure pore pressure and can assist in evaluating the performance of mine dewatering programs and any impacts from seasonal variations (Girard & McHugh, 2000).

Inclinometers are devices used to measure any underground movement of rock. The structures of an inclinometers consist of a casing that is inserted into the ground in the region where movements are expected, with the assumption that the end of the casing is immovable. To determine any movement, the lateral profile of displacement can be calculated from sensor data (Girard & McHugh, 2000), and it can be established whether the movement is constant, accelerating, or responding to any remedies (Osasan & Afeni, 2010).

A borehole extensometer is a device comprised of tensioned rods anchored at various intervals down the borehole. The displacement of the rock mass is quantified by measuring variations in the distance between the anchor and the rod head.

2.5.3 VISUAL INSPECTIONS

This method of slope monitoring is the least technically involved. It relies on the geotechnical/geomechanical engineer to carry out routine inspections of the pit, accessways, highwalls, and crests that are close to working areas and may pose a potential danger to people, equipment, and mine operations (Osasan & Afeni, 2010). Equipment operators and mine supervisors are also vital members of the efforts of visual inspections, they spend more time throughout the day in the pit than most people and thus could provide valuable insight. As inspections are carried out, the current inspection is compared to the previous one, and any changes that may be detrimental to slope stability should be noted. With the advance of new technologies like survey drones, more accurate camera sensors, and photogrammetry, this area of slope monitoring can benefit a lot from using these to reach areas of the pit that may be out of reach by engineers, equipment operators, and supervisors. It is in this area that this thesis work may contribute.

2.6 UNMANNED AERIAL VEHICLES (UAVs) IN THE MINING INDUSTRY

The use of drones has grown across a number of industries as shown in Figure 1. Drones can be applied to several industries for diverse tasks. Military and space exploration are the two main areas where unmanned vehicles of any kind have been widely used, and because of the incredible progress made in those industries, other industries such as mining, agriculture, construction, and wildlife management, just to name a few, have been able to adopt this technology and flourish.

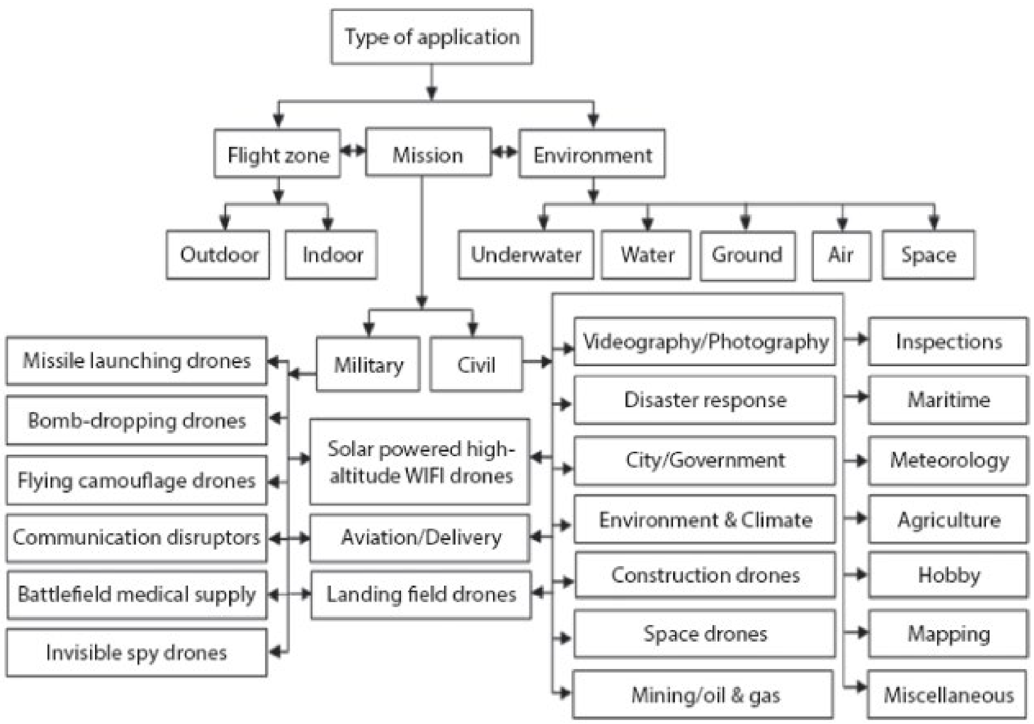

Figure 1 Different types of applications for UAVs (Darvishpoor et al., 2020)

When it comes to the mining industry specifically, drones have seen a wide range of applications. Unmanned aerial vehicles (UAVs) have the capacity to carry many payloads, including cameras with differing optical capabilities, thermal sensors, multispectral imaging cameras, and geophysical instruments like magnetic and radiation sensors. This versatility allows drones to be used for several purposes, including topographic mapping, stockpile volumetric surveys, and monitoring tasks such as slope stability surveys, tailings dams, and haul road surveys (Park & Choi, 2020). From these diverse capabilities, UAVs have been applied to three main functions of mine operations including topographic surveys, image data collection, and video data collection. The data collected from these three main functions can then be used to gain valuable insights into different stages in the life of a mine. The life of a mine is divided into five main stages, namely prospecting, exploration, development, exploitation, and reclamation, and in all these different stages the use of drone technology has been well documented.

Prospecting refers to the search for ores or other valuable minerals like coal and non-metallics (Hartman, 2002). It is divided into direct and indirect methods of determining the presence of minerals. The direct methods rely on physical geologic methods, where ore deposits can be visually examined as outcrops on loose fragments on the surface of the ground. The more valuable methods of prospecting are the indirect methods, which rely more on the science of geophysics and can be used to detect anomalies using physical measurements of seismic, gravitational, magnetic, electrical, electromagnetic, and radiometric variability of the earth. All these methods can be applied in many ways, one of them being through the air in terms of aerial photography to make geologic and photographic maps and airborne geophysics. In the past, larger aircraft were tasked with doing these duties, which are expensive and inconvenient in some areas, but drones are taking over those duties. (Eskandari et al., 2023) used a DJI Phantom 4 Pro UAV seen in Figure 2, to overcome terrain challenges when prospecting and exploring for podiform chromite deposits.

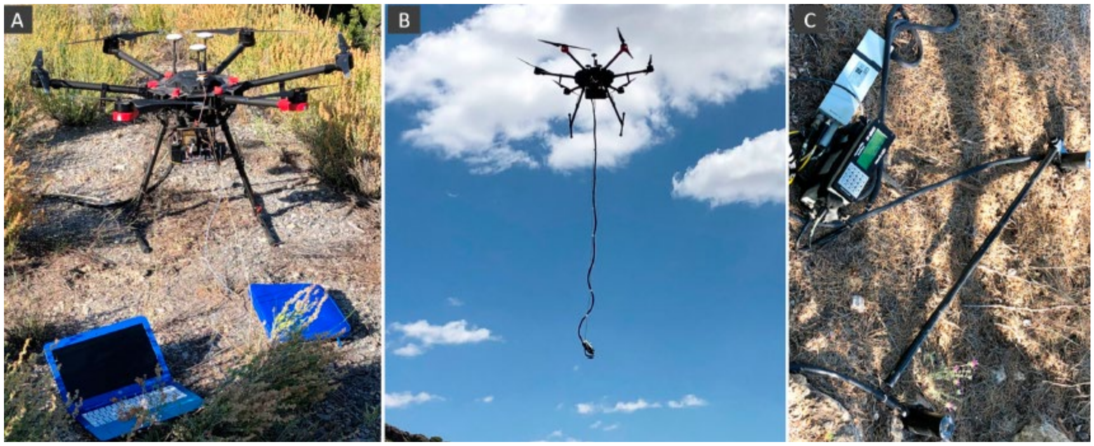

Figure 2 (A) a Mavic Matrice 600 Pro Hexacopter drone; (B) static drone position with the magnetometer hanging below; (C) base magnetometer for diurnal corrections (Porras et al., 2021)

The UAV allowed them to survey and acquire geotagged images which can be used for geologic mapping. (Porras et al., 2021) used drone magnetic surveys to detect the mineralization of copper, cobalt, and nickel in the Estancias mountain range of Betic in Spain. They relied on the DJI Matrice 600 Pro drone, with a mounted payload of a vapor magnetometer. The geophysical survey gave researchers valuable data about the mining potential of the area, and how future research activities should be designed there.

In the exploration stage, the objective is to further define the extent and value of the ore. It involves a lot of drilling, collecting assay samples for testing, estimating tonnages and ore grade, and making decisions on whether or not to abandon a project or move into the development phase (Hartman, 2002). Much like prospecting, the application of drones in exploration is mainly for image data collection, different kinds of camera sensors are used depending on the quality of image resolution required and the carrying capacity of the drone among others. (Park & Choi, 2020) outlines how UAVs employed in mineral exploration may be classified into two categories based on the type of data they collect: geological and structural study through remote sensing, and airborne geophysical investigation. Remote sensing is a science discipline that encompasses the acquisition, processing, and interpretation of images and associated data. These images and data are obtained from aircraft and satellites, and they capture the intricate interplay between matter and electromagnetic radiation (Sabins, 1999). A novel approach for the automated lithological categorization of open pit mines employing tiny unmanned aerial vehicles (UAVs) and machine learning (ML) algorithms was proposed by Brazilian researchers. They used a red, green, and blue (RGB) camera to capture images and initially classified materials according to visible geological features. They then coupled this with ML techniques such as k-nearest neighbour (KNN), random forest (RF), and support vector machine to name a few to produce a more precise method of classification as compared to manual classification (Beretta et al., 2019). (Heincke et al., 2019) endeavoured to create a multi-sensor unmanned aerial system (UAS) with the ability to collect magnetic and hyperspectral data. Using both fixed-wing and multi-copter UAVs, their objectives were to use the magnetic surveys to trace sub-vertical carbonatite veins in the area covered by overburden, establish if any, the relationship between those veins and the main mineralogy of the area, and through hyperspectral imaging identify possible manifestation of rare-earth elements in test outcrop areas.

Mine development is about opening up the orebody so that it is primed for exploitation, it involves setting up the required infrastructure and stripping the overburden to expose the ore. Mineral exploitation is the fourth stage of mining and refers to the actual recovery of the mineral from the earth. Traditional exploitation or mining methods fall into two categories; Surface or underground depending on the economics, geologic conditions, safety, available technology, and the orientation of the orebody (Hartman, 2002). The exploitation stage of mining is usually the longest stage in the life of a mine and it is in this stage that the most use from UAVs can be assessed. Table 2 below outlines the areas of activity where drones are being deployed in the mining industry, it is evident that the same type of data can be used for different objectives.

Table 2 Use of Unmanned Aerial Vehicles/Systems in Mining (Lee & Choi, 2016; Shahmoradi et al., 2020)

Area of Operation	**Type**	**Objective**	**Data Type**
Mine Technical	Mine Survey	Pit Progression	Topographic Survey - 3D Model, Pointcloud
		Dump and Stockpile management	
	Drill and Blast	Drill pattern design	
		Blast monitoring: Flyrock, dust, misfires	Image and Video
		Post blast surveys	
	Material Handling (Truck and Shovel Planning)	Run-Off-Mine (ROM) management	Topographic Survey - 3D Model, Pointcloud
		Material Sources and Destinations	
		Truck and Shovel material allocation	
	Ore Control	Drillhole sampling	Aerial Photographs - Orthomosaic, drillhole survey
		Shotmuck Inventory	Topographic Survey - Pointcloud
	Reconciliation	Volumetric calculations	Topographic Survey - Pointcloud
		ROM management	
Mine Operations	Dispatch	Fleet management	Topographic Survey - 3D Model
		Haulage systems	Topographic Survey - 3D Model, Pointcloud
		Water management	Aerial Photographs - Orthomosaic, Image and Video
	Mine Safety	Slope stability assessment	Topographic Survey - Pointcloud, 3D model
		Road maintenance	
		Emergency management	Aerial Photographs - Orthomosaic, Image and Video

In the area of drill and blast specifically, there are several researchers working on creating workflows around the use of UAVs. (Bamford, Medinac, et al., n.d.) concluded, after reviewing many research papers and work being done in the D&B that it can categorized into pre-blast monitoring, which concentrates on providing accurate information on the area to be blasted in terms of the ground's structural condition and the accuracy of drillhole placement. Following pre-blast monitoring is blast monitoring which occurs at the moment of firing the explosives. It involves the use of UAVs equipped with high-speed cameras to capture blasts as they occur and later analyze them possible misfires, Flyrock events, and dust spread. Post-blast monitoring as the final monitoring stage involves using UAVs for fragmentation analysis and assessment of the remaining highwalls so that improvements can be made to subsequent blast designs if needed. Table 3 below outlines some of the areas in drill and blast where drones have been implemented.

Table 3 Use of UAVs in drilling and blasting

Research Area	Drones Used	Payload Attached	Monitoring	Papers
Bench structural geology	UAV (unspecified)	RGB Camera	Pre and Post blast	(Stewart & Wiseman, 2017)
Topographic Survey	DJI Phantom 3 DJI Phantom 4	RGB Camera, RTK RGB Camera	Pre and Post Blast	(Beretta et al., 2018)
Topographic Survey	Sensefly eBee drone	RGB Camera	Pre and Post Blast	(Wiegand, 2016)
Drilling accuracy	DJI Phantom 4 Pro	GPS RGB Camera	Pre-blasting	(Mueller, n.d.)
Ground Vibrations	DJI Phantom 4 Pro	GPS RGB Camera	During Blast	(Bui et al., 2020)
Rock Fragmentation	DJI Phantom 3	RGB Camera	Post Blast	(Tamir et al., 2017)
Rock Fragmentation	Parrot Bebop 2	RGB Camera	Post Blast	(Bamford, Esmaeili, et al., n.d.)
Rock Fragmentation	DJI Phantom 4 Pro	camera	Post Blast	(Valencia et al., 2019)

2.7 ARTIFICIAL INTELLIGENCE IN THE MINING INDUSTRY

Artificial intelligence (AI) refers to the interdisciplinary field that encompasses the scientific and technical aspects involved in the development of intelligent machines, with a particular focus on intelligent computer programs. AI is closely connected to the analogous endeavour of employing computers to comprehend human intellect. However, AI is not obligated to limit its approach to methodologies that are biologically perceptible (Mccarthy, 2007). It combines computer science and robust datasets to enable human-like problem-solving (*WHAT IS ARTIFICIAL INTELLIGENCE?*). AI can be categorized as strong or weak AI. Weak AI is the driver of most of the AI advancements in the world today (*What Is Artificial Intelligence (AI)?*, 2023) where an AI is used to solve a specific problem or task. Under the umbrella of AI, several technologies have been created or improved upon with AI such as machine learning and deep learning as seen in Figure 3 below. Machine learning is a class of AI that gives computers the ability to learn from large amounts of data without any explicit instructions or program that allows them to do so (*Machine Learning, Explained*, 2023). Machine learning is centered around two interconnected inquiries: How can one develop computer systems that possess the ability to enhance their performance autonomously via accumulated experience? And what are the underlying principles of statistical computation and information theory that control the functioning of learning systems, including computers, humans, and organizations? (Jordan & Mitchell, 2015).

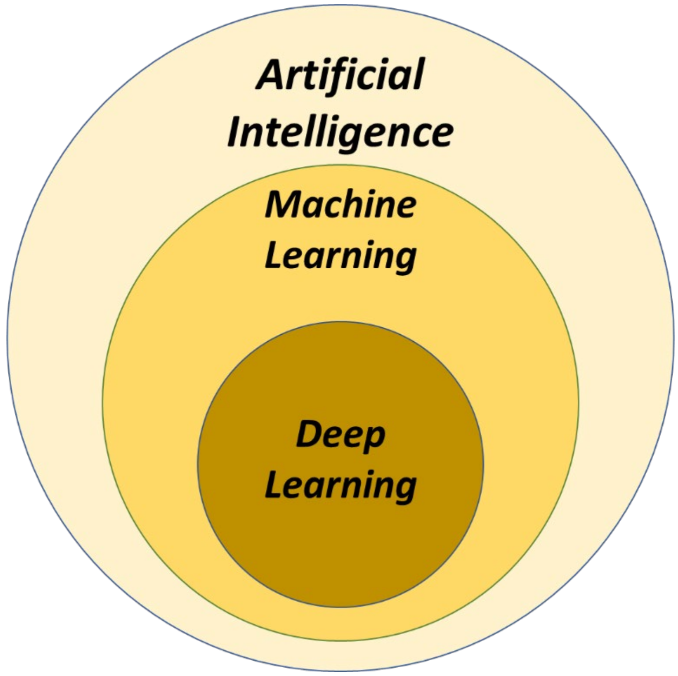

Figure 3 Relationship between artificial intelligence, machine learning, and deep learning

By addressing these two questions, computer scientists have come up with a technology in machine learning that can be applied to various problems by using large amounts of data and statistical techniques. To be able to accomplish this task, a machine learning model uses certain algorithms that are suited for the task at hand. An algorithm may be described as a precisely defined computational procedure that accepts one or more values as input and generates one or more values as output within a limited duration. An algorithm may be defined as a series of computer operations that systematically convert the given input into the desired output(Cormen et al., 2022). Regression models, decision trees, random forest, and neural networks are just some of the algorithms that are used in ML models(datascience@berkeley, 2020).

The neural network algorithm is among the more popular algorithms used in ML, it mimics the functionality of the human brain by using a large number of linked processing nodes to run information through which makes it suitable for pattern recognition, image or related visual data processing, and other recognition functions.

In recent years the mining industry has ventured into using AI and machine learning methods to enhance process understanding to better informed the decision making. In the day to day of a mine operation, there is a large amount of data being produced and historically this data has been stored without anyway of using it efficiently. By tapping into the concepts of AI, mine operations have the opportunity to gain new insights into the interconnectedness of their operations.

At the very beginning of mining, there is a great push to understand as much about the ground as possible, this is done through prospecting and mineral exploration where geophysical, geochemical, and aerial photography data is collected initially and then followed by different sampling methods such as drilling and excavations (Hartman & Mutmansky, 2002). In the past, these mine operators relied on statistical methods to analyse the data, but now research is shifting to more advanced AI methods. (Acosta et al., 2019) designed an ML framework to use a combination of hyperspectral data and high-resolution mineralogical data to map minerals on exploration drill cores. The cores are collected in 100s of feet and then sectioned into 3 ft cylindrical sections. The current methodology is to analyze the total length of these cores to determine mineral presence, which is resource consuming. The framework proposed in the research entails using hyperspectral image data obtained from some of the cores, combined with scanning electron microscope (SEM) images that contain mineralogy data as a classification mask to predict the mineralogy of the rest of the drill core length. Random forest and support vector machines are the ML algorithms used here and they produced good predictions according to the publication, producing an image than can be analyzed to produce an image that displays mineralogy data. Another researcher investigated the use of drill core images to determine the Rock Quality Designation (RQD) of the rock mass as shown on Figure 4. RQD is a measure of the proportion of the core length that is recovered in pieces greater than 10 cm (3.93 inches), relative to the entire length of the core drilled during a particular operation (Carlos et al., 1987), it is an important metric in mining used to determine how intact the ground is and thus how mining operations should be conducted.

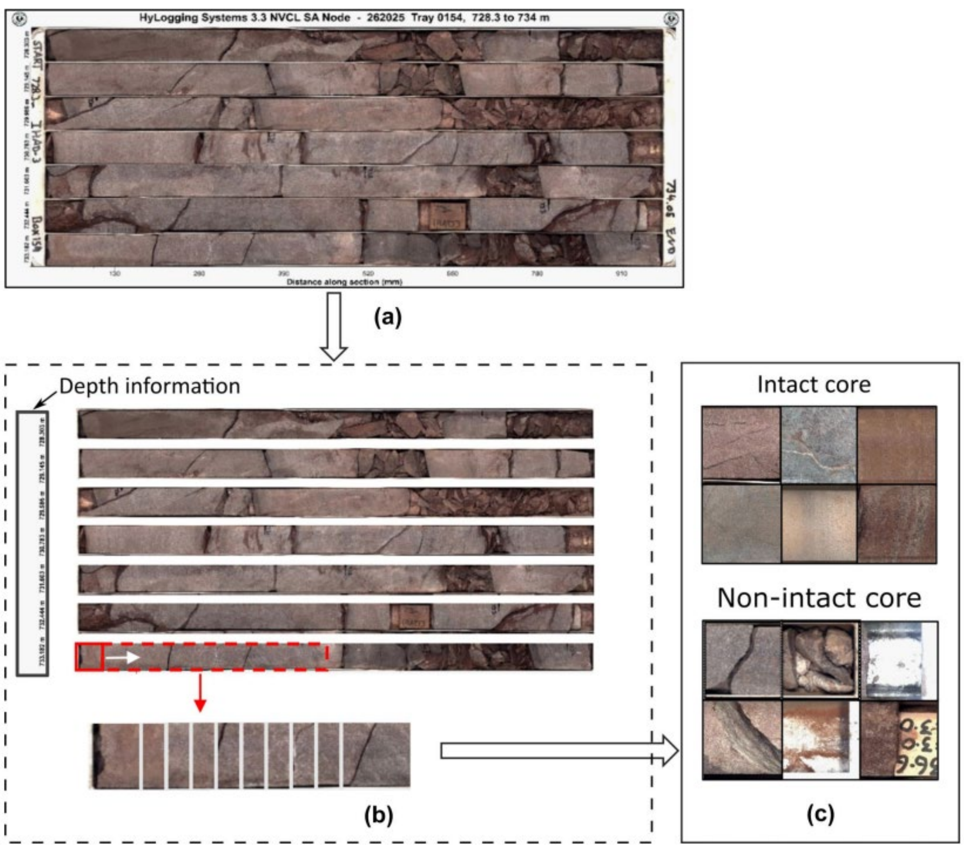

Figure 4 Procedure of creating small square images (SSIs) to train and test the CNN model: (a) input tray image with core depth of each row of the tray shown on the vertical axis; (b) Illustration of row depth detection, row separation, and defining the SSIs; (c) manually labelled SSIs from the two classes. In this example, seven depths were detected using OCR and thus the tray was separated into seven rows (F. Alzubaidi, Mostaghimi, et al., 2022)

The researchers in this study used a standard convolutional neural network (CNN), which will be described in more details in later chapters, made up of four convolutional layers, one fully connected layer and an output layer. They also employed hyperparameter optimization which is a great way to determine the best user selected parameters for setting up the CNN model.

As a mining operation develops onto the production stage, there are more opportunities to apply machine learning and deep learning technology. Drilling and blasting is one of the areas in mine operations were several ML techniques have been applied to attempt to correlate the controllable input parameters of D&B such as burden and spacing, drillhole depth, blasthole diameter, stemming length, and drilling pattern, with the outputs such as fragmentation, ground vibrations, muckpile geometry, airblast, and backbreak (Carlos et al., 1987) in order to optimizer parameter selection. Often times the values set for these parameters are not achieved during execution in the field, drillholes might be drilled short, or in wrong location and angle, amount of explosives used might be excess, or blastholes may not be properly confined due to short stemming column. (Valencia et al., 2022) Investigated the use of support vector machines and CNNs to detect the exact location of drillholes from images and compare these results with the what was designed. This assists engineers determine if the as drilled drillholes match up to the design parameters so that they can adjust the other parameters such as amount of explosives used, to ensure that the designed output is still achieved, drilling errors withstanding. Fragmentation is the most important outcome of D&B that has a great impact on the downstream operation, so it is imperative to have an accurate determination of how well a blasting instance fragmented the rock. One research group (Yaghoobi et al., 2019) used a multi-layer perceptron (MLP) neural network to determine the fragmentation distribution after a blast. Instead of using images directly in the ML model, they used feature extraction methods such as Fourier transforms, Gabor, and wavelet method to extract visual features which were made into input vectors for the MLP algorithm. The output of the ML model was compared with the traditional method of using split-desktop software in manual mode, the results showed that this MLP combined with the feature extraction methods had great accuracy and was better than the automated mode of split-desktop in use now.

As mentioned in the previous sections, rock fragmentation is important to the rest of the downstream processes, but there are other metrics such as backbreak, flyrock, and ground vibrations that is used to measure the success of blasting. A lot of researchers have looked into these outcomes and have endeavoured to connect them to the inputs using machine learning combined with mathematical optimization methods. The work flow of most of these research areas involve using drill and blasting parameters as inputs to a machine learning model, mostly a variation of the neural nets model, and then utilize optimization methods such as genetic programming (GP), ant colony optimization (ACO), and particle sawm optimization, to optimize the selection of hyperparameters that may give the best results from the ML model. These applications do not depend on images as input data, but they serve as a great indication on the push for adopting machine learning methods into the mining industry in order to gain more insight on the operation and extract more usefulness for the data the industry generates. Table 4 below outline some of these research areas that has been explored in this area.

Table 4 research areas were machine learning has been implemented in mining. The inputs represent blasting parameters; B-Burden, S-Spacing, ST-Stemming, D-Hole Diameter, L-Hole Length, SD-Specific Drilling, H-Bench Height, J-Sub-Drill, CL-Charge Length, CLR-Charge Last Row, NR-Number of Rows, Pf-Powder Factor, Ch-Charge per Delay, SC-Specific Charge. The ML and optimization models used here are ANN-Artificial Neural Networks, RF-Random Forest, GA-Genetic Algorithm, GP-Genetic Programming, ACO-Ant Colony Optimization, ABC-Artificial Bee Colony, HHO-Harris Hawks Optimization, SCA-Sine Cosine Algorithm, MLP-Multi-Layer Perceptron, ANFIS-Adaptive Neuro Fuzzy Inference System, SVM-Support Vector Machines, BP-Back Propagation, RBF- Radial Basis Function, GWO-Grey Wolf Optimizer, XGB-Extreme Gradient Boosting, PSO-Particle Swarn Optimization.

Papers	ML model	Input	Output	MSE/RMSE
Monjezi et al., 2010	GA-ANN	D, L, S, B, T, Pf, SD, Ch, RMR	GA-hyperparameters selection	
			Flyrock	0.327
			Backbreak	MSE=0.009
Shirani Faradonbeh et al., 2016	GP	B, S, ST, Pf, SR	Backbreak	0.327
Saghatforoush et al., 2016	ACO-ANN	B, S, L, ST, Pf	Backbreak	
Ebrahimi et al., 2016	ABC-ANN	B, S, L, ST, Pf	Flyrock	0.530
Zhou et al., 2021	HHO-RF	B, S, L, ST, Pf, SD	Backbreak	0.106
	SCA-RF			0.0997
Esmaeili et al., 2014	MLP-ANN	H/B, ST, SC, DN, NR, CLR, S/B	Backbreak	0.880
	ANFIS			0.600
Mohammadnejad et al., 2013	SVM	B, S, L, SD, ST	Backbreak	0.340
Sayadi et al., 2013	BP-NN	B, S, L, ST, SC, SD	Backbreak	0.221
			Fragmentation	0.067
	RBF-NN	B, S, L, ST, SC, SD	Backbreak	0.311
			Fragmentation	0.112
Nabavi et al., 2023	GWO-XGB	B, S, ST, D, H, SC, NR	Backbreak	0.010
	PSO-XGB			
Monjezi et al., 2013	BP-NN	B, NR, Pf, S/B, ST/B, CLR, Ch	Backbreak	0.643
Ghasemi, 2017	PSO-Linear	B, S, ST, Pf, SR	Backbreak	0.353
	PSO-Quadratic			0.279

2.8 SEMANTIC SEGMENTATION

To comprehend the concept of semantic segmentation, it is important to have a foundational understanding of computer vision. Computer vision is an integration of principles, methodologies, and theories derived from digital image processing, pattern recognition, artificial intelligence, and computer graphics (Wiley & Lucas, 2018). It facilitates the ability of computers and systems to extract significant and valuable insights from digital photos, videos, and other visual inputs. These insights can then be utilized to provide suggestions based on the acquired information (*What Is Computer Vision?*, 2023). For computer vision to be a possibility it relies on two main technologies that are subfields of machine learning, these are convolutional neural networks (CNN), and deep learning.

Convolutional neural networks got the first part of its name from the mathematical linear operation between matrices called convolution, and neural is derived from the way in which it mimics how neurons in the human brain interact with one another. CNN learning models are made up of node layers namely the input layer which takes in the initial input data of the model, hidden layers which make up the middle part of the network and where all of the computation of the learning model occurs, a CNN can have more than one hidden layer, and an output layer which produces the results of the model (*What Are Convolutional Neural Networks?*, 2023). The CNN model uses three types of layers: convolution, pooling, and fully connected layers.

The Convolutional layer is the initial and important element of the CNN architecture. It is made up of a collection of filters or kernels that execute a convolutional operation on the input data, which is usually in vector format (L. Alzubaidi et al., 2021). The filter itself is made up of a 2-D array of numbers or weights and as it moves across the image executing the convolution operation (Figure 5), which involves the computation of a dot product between the input pixel values and the filter, it detects features in the input layer and outputs a feature map which is then fed through other layers in the CNN(*What Are Convolutional Neural Networks?* 2023). Operations carried out in these CNN layers are governed by hyperparameters that the user has to define beforehand, for the convolutional layer the size and number of kernels, stride of the kernel, and padding have to be set. The stride of a kernel or filter is the distance between two consecutive filter positions as it traverses the input data, while padding is a method used to preserve the shape (height and width) of the input array at the same time allowing the kernel to reach the elements in those corners by adding rows and columns to the input array (Yamashita et al., 2018). Zero padding, adding rows and columns of zeros, is the most common method of padding.

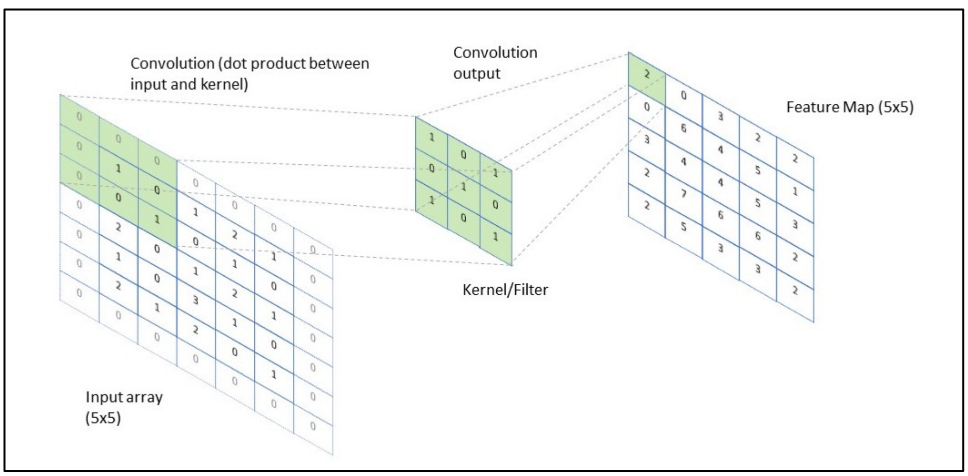

Figure 5 Example of convolution operation with zero padding

One convolutional layer can be followed by another convolutional layer, but at some point, a *pooling layer* is inserted in the CNN. The objective of the pooling layer is to sub-sample or shrink the feature map that was created in the convolution layers (L. Alzubaidi et al., 2021), this will reduce the number of learnable parameters and computations in the network (Jha & Sahu, 2020), which in turn helps to prevent overfitting the model to the current data and allows for faster training. There are two main pooling methods, these are max pooling and average pooling. Max pooling takes the maximum value from the region of the feature map that is within the pooling window, thus capturing the most noticeable features. While average pooling calculates the average of the values in the pooling window, which provides an average feature representation of the feature map (A. Kumar, 2023). Similar to the convolutional layer, certain hyperparameters in stride and size have to be selected by the user for the pooling layer.

Lastly, there is the *fully connected layer*. This layer is found at the very bottom or end layers of a CNN (Bhatt et al., 2021), each node in the output layer connects directly to a node in the previous layer, hence the name fully connected (*What Are Convolutional Neural Networks?*, 2023). A fully connected layer receives its input from the final output of a pooling or convolutional layer that came before it, but before the fully connected layer can take this data as input it has to be flattened. Flattening entails transforming the 2-D array output from the last pooling or convolution layer into a vector. It is in this layer that, based on the features that have been extracted from the operations performed by the convolutional and the pooling layers, a classification of some kind can be made.

The combination of these three types of layers will differ across the board, one or two convolutional layers may be paired with one pooling layer, or vice versa, and this leads to several CNN architectures with varying capabilities of processing data. Figure 6 below is an example of a CNN model.

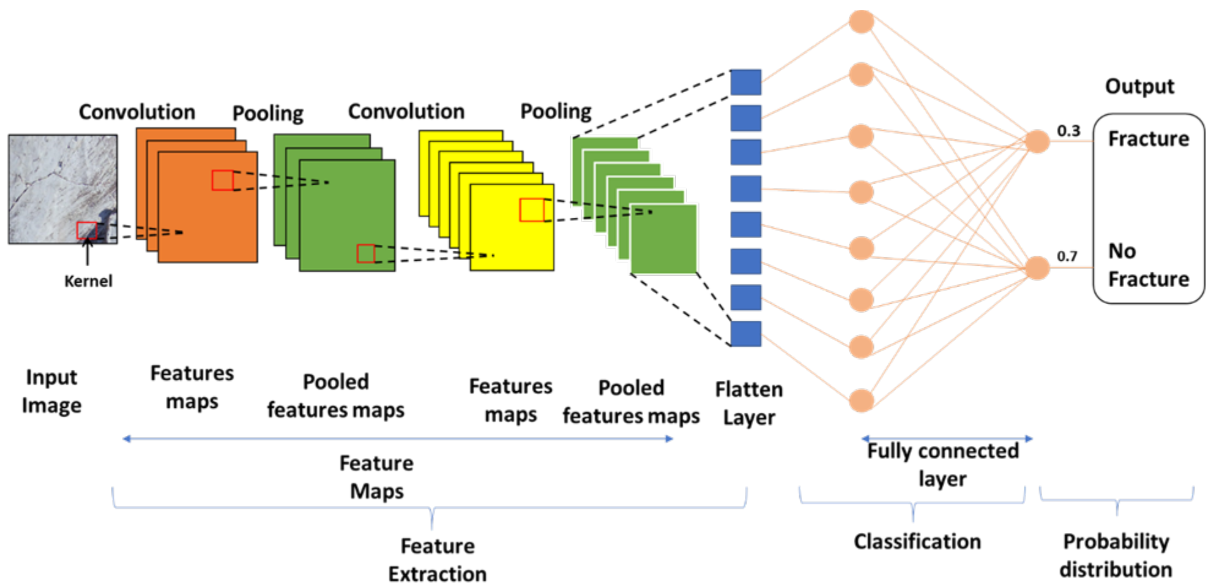

Figure 6 A typical Convolutional Neural Network model (Shah, 2022)

Deep learning is a subfield of machine learning. Deep learning models are essentially the same as the neural networks explained above, the only difference is deep learning models will have three or more types of layers(*What Is Deep Learning?*, n.d.). Deep learning allows for the nonlinear processing of data in multiple layers where the current layer takes the output from the previous layer as input(Vargas et al., 2017).

With those two concepts explained, it is easier to understand how semantic segmentation works. Semantic segmentation, a computer vision task, facilitates the assignment of class labels to individual pixels within an input image. Subsequently, these assigned labels serve as the basis for the model's segmentation of the image, delineating distinct regions corresponding to the specified class labels. The usual output of a segmentation model is the segmented image and a masked image of the different segmentation labels. Figure 7 is an example of the expected output of a semantic segmentation model.

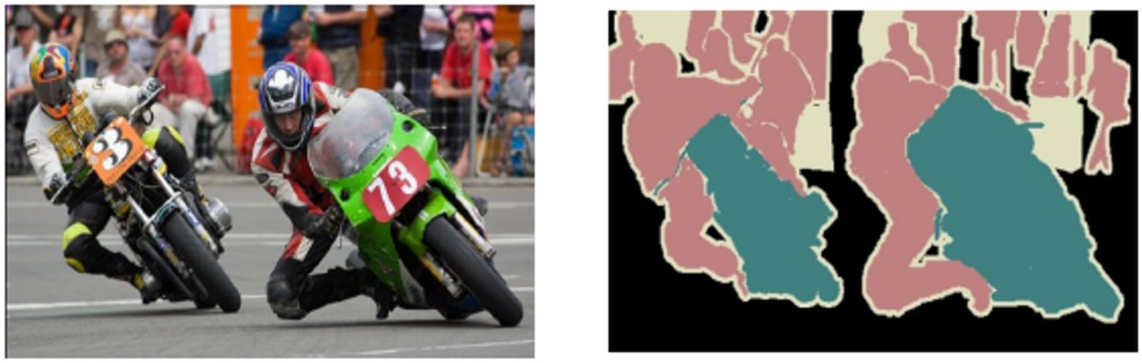

Figure 7 Given an image, a segmentation algorithm should output which pixels belong together semantically (Guo et al., 2018)

2.8.1 FULLY CONVOLUTIONAL NETWORKS

Fully convolutional networks are CNNs with the fully connected layers replaced with more convolutional layers, resulting in an end to end convolutional network (J. Long et al., 2014), which allowed the model to have much better accuracy results (Lv et al., 2023).The system consists of two components: a down-sampling section and an up-sampling part. The down-sampling section consists of convolutional layers, pooling layers, and dropout layers. Conversely, the up-sampling section has deconvolutional layers. The down-sampling component is, in fact, a highly intricate convolutional network of 19 layers. The essential innovation of FCN is the up-sampling component, which reverses the down-sampling process and results in a dense forecast (Yang et al., 2018). The dense output of Fully Convolutional Networks (FCN) is different from the classification output of typical Convolutional Neural Networks (CNN). The up-sampling component integrates both global and local information by including particular layers from convolutional and deconvolutional layers. The local information in the preceding convolutional layers mostly provides information about the identity of the item, whereas the global information in the deconvolutional layers primarily provides information about the location of the object. One advantage of this integrated structure is that it simultaneously deals with identification and localization issues. Additionally, the up-sampling component expands the classifications obtained from down-sampling to match the size of the original image, resulting in input and output images of the same size. Hence, the distinctive architecture guarantees the capability of FCN to effectively handle pictures that have several scales and levels.

Using FCNs as the basis, several deep learning neural networks have been proposed for semantic segmentation such as UNet, DeepUNet, ResUNet, and DenseNet just to name a few (Singh et al., 2020). This deep learning model has been used in a variety of settings such as medical imaging to advance computer added diagnostics, civil construction for structural inspections, and parts manufacturing for detecting defects. The U-Net created by (Ronneberger et al., 2015) is one of the more popular image segmentation models and has been adopted and modified by many to tackle different kinds of segmentation problems. The first iteration of the U-Net model from the researchers listed above was motivated by the ability to use a small dataset of biomedical images effectively to train a deep learning model, which at that point had been a challenge. Another group of researchers in civil industry investigated the use of these models in identifying cracks on transportation infrastructure such as asphalt and concrete as a sign of aging. The researchers grouped their findings into 10 groups based on the genesis of the model architecture used for that particular crack detection method, this includes FCN, U-Net, encoder-decoder model, and a few unsupervised learning methods (Li et al., 2022).

In the mining industry, there has been a modest application of image segmentation. One researcher looking into the characterization of drill cores used the R-CNN model to segment fractures in the drill cores, that might indicate real world fractures. R-CNN is an instance segmentation model that can localize, classify and segment objects, by combining both object detection and semantic segmentation (F. Alzubaidi, Makuluni, et al., 2022). Tension cracks, mentioned in section 2.5.1 earlier is another slope monitoring concern, (Winkelmaier et al., 2021) used aerial imaging, U-Net, and E-Net models to attempt to identify these tension cracks that occur on the crests of mine benches. The models performed well at localization of the mine benches, but struggled a bit when it came to identification of the tension cracks themselves.

2.9 MODEL EVALUATION

The evaluation of model performance holds significant importance in gauging the efficacy of deep learning architectures, specifically in the realm of semantic segmentation tasks, where fully convolutional models such as the U-Net demonstrate exceptional proficiency. This section elucidates the methodologies utilized for model evaluation, with the objective of furnishing a comprehensive comprehension of the metrics and techniques imperative for assessing the model's efficacy.

In the realm of fully convolutional models tailored for pixel-wise predictions, the evaluation of model performance transcends conventional classification metrics and encompasses the meticulous assessment of spatial segmentation accuracy. The evaluation metrics employed encompass Intersection over Union (IoU), equation (1), which quantifies the degree of overlap between the predicted and ground truth segmentation masks, and the Dice Coefficient, which evaluates the similarity between these masks.

The utilization of a confusion matrix is of utmost importance in providing a nuanced and exhaustive overview of model predictions, adeptly breaking down the results into true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). The matrix mentioned above assumes a crucial role in the computation of diverse metrics, encompassing but not restricted to Intersection over Union (IoU), Precision (P_r), Recall (R_e), and F1 score.

$$IoU = \frac{TP}{TP+FP+FN} \tag{1}$$

These metrics are crucial in providing intricate insights into the efficacy of machine learning models, especially in situations where there exist imbalanced class distributions or varying implications of false positives and false negatives, thereby requiring a comprehensive evaluation(Yu et al., 2023). Precision, denoted as the ratio of accurately identified positive instances to the sum of accurately identified positive instances and erroneously identified positive instances, functions as a comprehensive metric evaluating the model's efficacy in generating precise positive predictions.

$$Precision(P_r) = \frac{TP}{TP+FP} \tag{2}$$

Recall, alternatively referred to as sensitivity or true positive rate, assesses the model's proficiency in capturing the entirety of positive instances within the dataset.

$$Recall(R_e) = \frac{TP}{TP+FN} \tag{3}$$

The F1 score, which is a composite measure derived from the harmonic mean of precision and recall, functions as a unified metric that effectively manages the delicate balance between false positives and false negatives.

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{4}$$

Other important metrics include pixel accuracy and the Dice coefficient, which is similar to IoU. These serves as a means to quantitatively assess the proportion of accurately predicted pixels in relation to the overall number of pixels. The aforementioned metrics offer spatially sensitive evaluations, which are of paramount importance in the context of semantic segmentation tasks.

$$Dice = \frac{2 \times TP}{2 \times TP + FP + FN} \tag{5}$$

$$Pixel\ Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

In addition to employing quantitative metrics, it is imperative to engage in visual scrutiny of model predictions compared to ground truth masks. This practice is indispensable for comprehending the model's inherent capabilities and potential limitations, particularly in its ability to capture intricate features that may pose challenges in numerical quantification.

In summary, the comprehensive assessment of fully convolutional models, such as the U-Net, necessitates the adoption of a multidimensional methodology that encompasses spatially conscious metrics, visual scrutiny, and cross-validation methodologies. The evaluation framework that has been proposed not only quantifies the accuracy of the model, but also offers valuable insights into its capacity to capture spatial dependencies that are critical for semantic segmentation tasks. The present evaluation methodology, which is characterized by its comprehensiveness, serves to enhance our understanding of the model's performance in real-world scenarios, thereby contributing to a more nuanced comprehension of its efficacy.

2.10 EDGE DETECTION

Edge detection is one of the older and important methods under the umbrella of computer vision. It can help provide additional information for many visual tasks including image recognition, image segmentation, face recognition, medical tracking, and others (Jing et al., 2022). Edge detection in computer vision refers to a process of capturing properties such as discontinuities in the photometrical, geometrical, and physical characteristics of objects in images (Ziou & Tabbone, 1998). Classical edge detection methods have a similar operation as the convolutional layer in CNNs, they depend on the mathematical operation of convolution. A 2-D filter or kernel will convolve the input image and it will be sensitive to large pixel value changes in the image while returning a zero value for regions of uniform pixel values (Ziou & Tabbone, 1998). There are several edge detection methods that have been developed over the years, (Shrivakshan & Chandrasekar, 2012) outlines the different edge detections such as Sobel, Prewitt, and Canny edge detectors that have shown some benefit in various applications. Edge detection methods fall under the umbrella of computer vision methods, thus it makes it simple to compare the effectiveness of any one method using similar metrics (Tariq et al., 2021) as the deep learning methods of image segmentation. In this thesis work, edge detection methods were looked at as a method of comparison between more classical methods of identifying and segmenting objects and advanced technologies such as deep learning and CNN models.

CHAPTER 3 : **METHODOLOGY**

This chapter will present the details of the research approach by describing the process of selecting locations for data collection and the UAVs along with required software needed for aerial photogrammetry. This chapter will also adventure into how the collected data was pre-processed before any training or detection of fractures can be done. This chapter will close of by looking at the segmentation models used and the parameters selected to obtain the best segmentation results possible.

3.1 DATA COLLECTION

The first part of collecting data is determining the best location to do so. This thesis work is completed under a broader project funded by NIOSH which had goals to build up the capacity of well-trained mining professionals to help the industry advanced in safety and technology. Due to this large project, there were a number of collaborations set up with other mining schools and the industry at large. Unfortunately, during that time, the Covid pandemic came to pass and this has made access to mine operations and their data a lot more difficult due to a number of safety and security concerns. Despite these challenges, quality data was secured at some mining operations located in Nevada around the Reno area and Arizona.

In Nevada data was located at an aggregates quarry in the Reno-Sparks area. The Sierra Stone Quarry is owned and operated by All-Lite materials which provides aggregate materials around North Western Nevada area. It is located in Storey County, seen in Figure 8, which has a rich mining history like most parts of Nevada, it has been operating since 1989. The quarry sits on rhyolite intrusive rock with lithology including Igneous, Hypabyssal, Felsic-hypabyssal, and Hypabyssal-rhyolite from the Eocene to Miocene geologic epochs(*Nevada Mineral Explorer*, 2021).

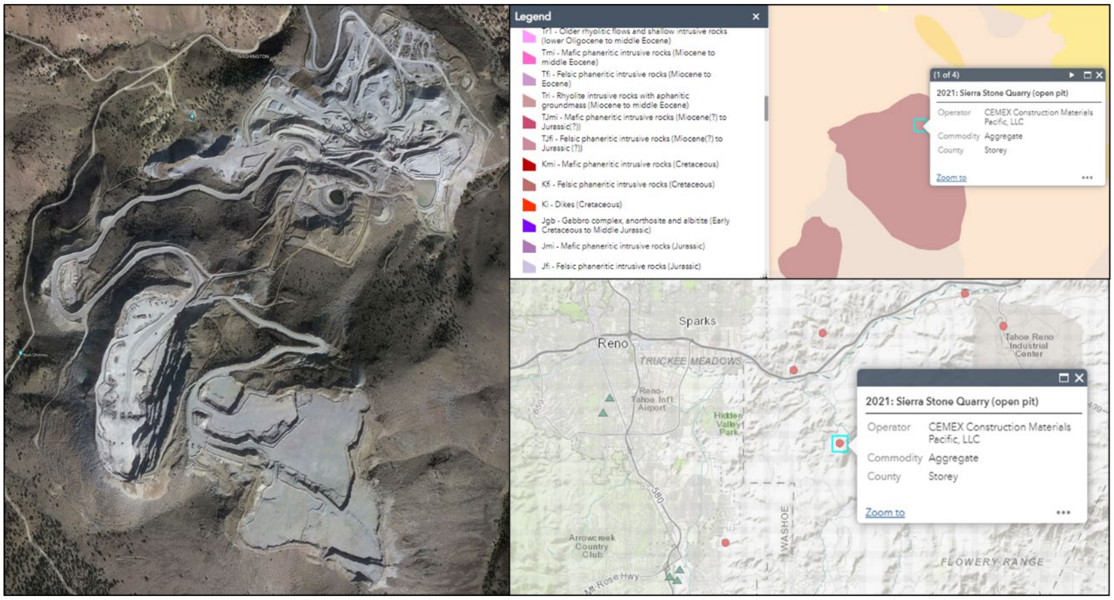

Figure 8 Location and geology information on Sierra Stone Quarry from Google Earth and (*Nevada Mineral Explorer*, 2021)

From the inception of the operation until recent years, Cemex Construction Materials (Previous owner) and All-Lite Materials operates this quarry as an open pit mine follow the normal mining process of drilling, blasting, loading, and hauling which was explained in earlier chapters. However, as the rock material and thus rock properties in the pit changed, they switched the from drilling and blasting to ripping and pushing with a dozer because the current pocket of material they are mining is softer and doesn’t require a lot of energy to break up to break up. For this thesis work, studying areas that have experienced blasting was important because that is the method of operation that is more common in the industry and thus would allow the findings of this work to be applied more broadly to the industry. Because of this desire for broad appeal, data was collected only in those area of the mine/quarry where drilling and blasting was done in the past.

There were two other mine sites identified for this project in Central and Southern Arizona. Both these mines are copper mines and similarly employ the normal four cycle mine operation. Due to the distance of the mines from the University and some company policies, it was difficult to arrange for researchers to go to the field themselves to collect data. Data sharing agreements were put in place between all parties, but adopting the data approved for sharing with the university to the data collection requirements described further below was challenging and thus most of that data proved to not be useful for the outlined approach.

3.1.1 IMAGE COLLECTION USING UAVs

After the location was established, the next step was to plan for data collection and then head out to the field to execute. As stated above this thesis work is part of a bigger project funded by NIOSH and with the assistance from those funds, the Mining and Metallurgical department here at University of Nevada, Reno has been able to secure several drone equipment for use in a number of projects. Table 5 outlines the drones that were available for the project and the different payloads they take. Payload in drone terminology refers to the weight a drone can carry, it is usually some kind of sensor or camera.

For this study, three drones were selected for use, these were the Phantom 4, Mavic Pro, and Matrice 100 seen in Figure 9, Figure 10, Figure 11 below. The Phantom 4 and Mavic Pro have fixed payloads that cannot be substituted for others, which make the less adoptable to different task requirements. With that said, they are both very robust drones and because of their simplicity, are easier to use

Table 5 UAV collection in the University of Nevada, Reno Mining department

Drones	Features and Payload
 *Figure 9 Phantom 4 Pro*	-1-inch CMOS sensor 4K/60fps videos, 20MP photos -Five directions of obstacle sensing -Remote controller with a built-in screen
 *Figure 10 Mavic Pro*	-1/2.3" (CMOS), Effective pixels:12.35 M
 *Figure 11 Matrice 100*	-Takes different kinds of payload sensors

overall. The DJI drone manufacturer, makes the drones listed above, they have a unique developer's platform that allows some of their drones to be adopted to research, or any professional discipline of their users. The Matrice 100 is one of those drones and for this project, it was put together from scratch, as DJI ships these types of drone unassembled. This allowed for the drone to be configured in a way that suited this study and the various other project in the research, mainly a bigger more robust mounting plate was use for the body of the drone to allow it to carry a variety of payload sensors and cameras. A normal RGB camera was used for this study.

After selection of drone systems to use, the next step was to select the drone in-flight control application. The use of UAVs has become ubiquitous in many industries in the past decade or so, (Darvishpoor et al., 2020) outline a lot of the ways different industries have changed their modes of operations to incorporate drones for faster, more efficient, and safer way of data collection. This growth has led to the development of a whole new industry centered around not only developing drones but the flight control software needed to rely commands to drone so that they can successfully complete the desired tasks. It is this area that the DJI drones excel, they are compatible with a lot of third-party drone flight applications, and through the DJI developer platform, researchers and other professionals can design and deploy their own applications to operate DJI drones. With that said, the important factors to considered when selecting the appropriate application for this research was whether or not it is compatible with the drones the department currently has, the different tools the application has and if they can be useful in simplifying data collection, and the cost. Cost is an especially important consideration because for a system like this to be implemented in the industry, its benefits must outweigh those of current methods, particularly cost.

The drone flight applications which were used for this research were Pix4D, UgCS (Figure 13), and the DJI drone application (Figure 12). The DJI drone application does not have a lot of functionality apart from providing feedback about the health levels of the different hardware systems on the drone and the controller, so it is necessity regardless of which other application is being used for data collection.

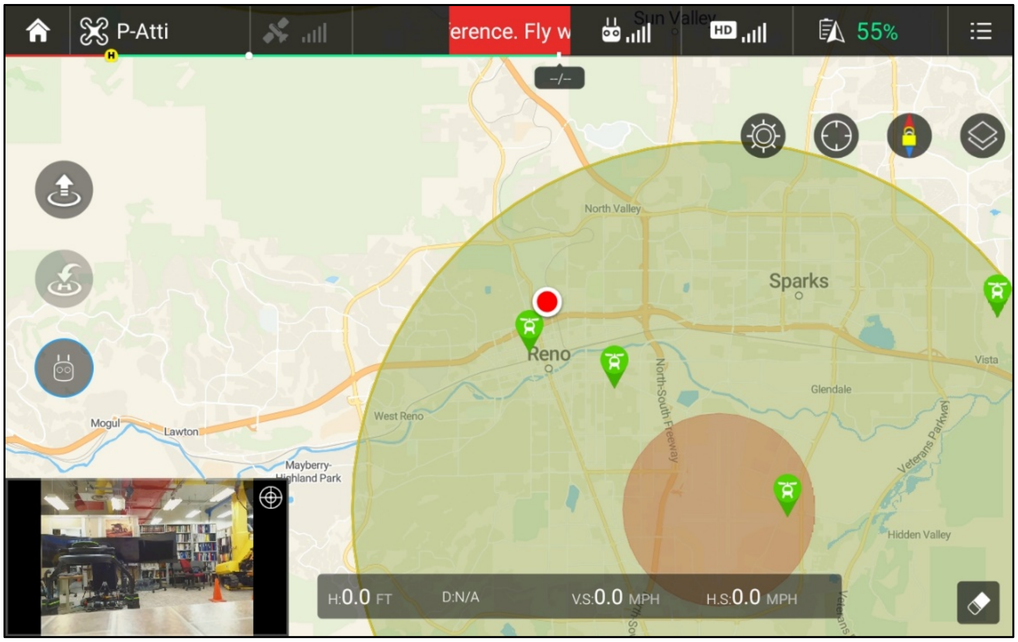

Figure 12 User interface of the DJI GO drone application

UgCS is a drone flight planning software developed by SPH Engineering (*UgCS Flight Planning*, 2023), its usage includes LiDAR surveys, mining, photogrammetry, vertical inspections, magnetic surveys just to name a few. UgCS is a detail driven application, during the mission planning mode, it gives the user the freedom to adjust a lot of parameters that many other applications automate on the background. Two important features it has is the vertical inspection and the simulator tools. Accurately surveying highwalls can be a difficult task for most drone applications, this is because the camera angle and flight paths allowed in those applications do not allow for maintaining a 90° angle with a vertical feature and surveying it in the vertical plane. But with the vertical inspection tool, is easy to set up a flight path that traverses the highwall from top to bottom, take high quality images at a 90° angle with the highwall which allows for most of the features to be captured accurately. After designing the flight path, UgCS has a flight simulation tool were details about the drone to be used can be entered and it will run a visual simulation so that the operator can have some sense of how the drone will perform in the field. Like anything else UgCS has its downsides, one of the main issues experienced during this research was that when operating in poor network environments, which is expected in mining, the application is difficult to connect to and update any prior flight plans. It is in this area were older applications like Pix4D excel, it was chosen as a backup in the field for the unfortunate scenario where using UgCS might not be possible. Pix4D does not have the same vertical inspection tool as UgCS, but it does have a free fly tool which was useful for manual drone operation as a last resort.

Figure 13 User interface of UgCS drone application. The green rectangle is the parameter of the drone flight path.

The different flights conducted for this data collection can be seen on Table 6 below. The intention was to collect images at different times of the day to diversify the image dataset which is an important attribute of a good training dataset.

Table 6 Flight missions carried out at the mine

Flight mission	Drone	Batteries used	Images	Flight time (min)	Type	Time of day
1	Mavic Pro	2	806	28	manual	morning, 10 am
2	Matrice 100	3	986	62	Auto, manual	Afternoon, 2:30 pm
3	Phantom 4	1	154	9	Auto	Afternoon, 3:30 pm

3.2 DATA PRE-PROCESSING

One of the most time-consuming steps about using AI techniques for any objective is the data pre-processing steps. Working with AI or deep learning is particularly requiring a large amount of data to get a well-trained model, and for most of these models receiving accurate information to be trained on is especially important. Thus, the two main objectives of data pre-processing for this study and many like it, are ensuring there is enough data available for training and making sure those data meet input requirements in terms of size and other image specific accuracy measures.

The first step for this project was to go through the 1899 images that were collected to ensure that the crack of fracture feature that is the center of this research work was present in the images collected. A number of images were discarded from this first step. The next step was to verify that the image sizes were appropriate for inputting into a CNN type model. Image resizing is a common step in the process of training these models, the size of the image has a relationship with the amount of features a the model can extract from the image, and the speed of training for the model (Wang et al., 2020). (Wang et al., 2020) also found that most deep learning neural networks use an image size of 256 X 256 pixels as default while others go as high as 640 X 640 pixels. Three different images sizes were captured during the data collection of this project corresponding to the different drones used, these were in the 4000 X 3000 pixel or higher range and thus would need to resized. The first approach was to use the image resizing tool in MATLAB which has the ability to resize images using different methodologies (MATLAB, 2023). Using this approach did not yield the best results because of the nature of the features in the images, so of the images had cracks that were barely visible as it is and the resizing methods available may lead to more challenges down the line. The method that was settled on was image tiling, this is a simple method of extracting smaller images of specified dimensions from a larger image while ensuring that all original pixels are accounted for in the smaller images. This was a good why of achieving the desired images size of 640 X 640 pixels. After this process about 1100 images were selected for further processing.

To train a model, the required dataset is the images that have the feature of interest and image masks (Singh & Rani, 2020). Image masks are created by taking the original image and assigning different pixel labels, the pixels that are associated with the object of interest are assigned a label of one and the background or other objects that are not part of the object of interest are assigned a label of zero. This allows for localization of the object of interest and the ML model will better learn the features that make up the object of interest. There are many tools that are available to use for image annotation or labeling, (Sager et al., 2021) outlines several of them, some of which were manual, semi-automated, and open source or not. The tool that was used for annotating images in this study was the Computer Vision Annotation Tool (CVAT) developed by Intel. CVAT is an open source tool that allows for image labeling for different applications in computer vision, it has several instruments for labelling that make it easy to use and one big feature is that it allows for team collaborations on annotation tasks (Rehman et al., 2021). This team feature allows for the project leader to assign different images to others for annotation and is then able to track their work, making corrections as needed. The output of CVAT is the binary mask coupled with its corresponding image as seen in Figure 14, which is exactly what is needed to input into a training model.

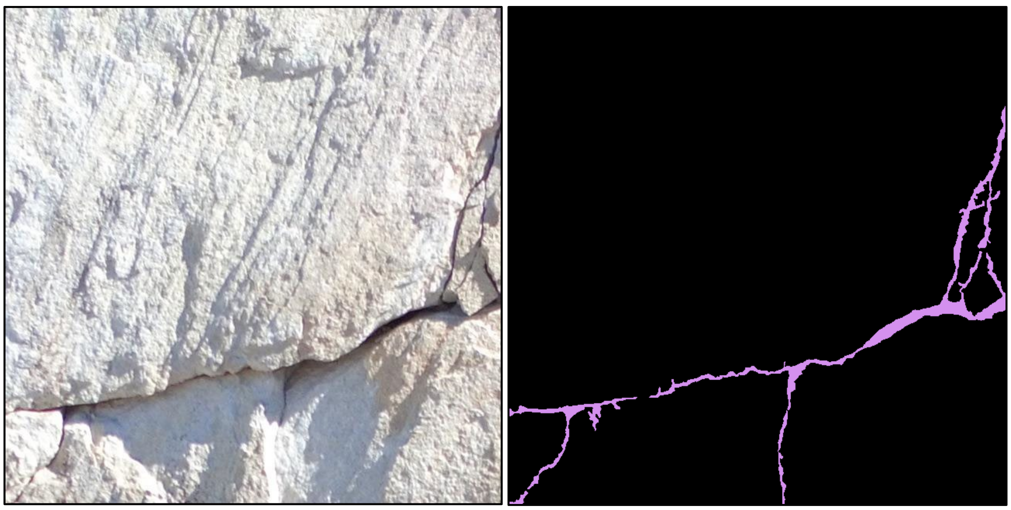

Figure 14 Output of CVAT annotation. Original image on the left and the segmentation mask on the right

After annotation of the available images, the next step is an image augmentation process. Deep learning and other machine learning models require a large amount of data for training (Singh & Rani, 2020), as a substitute for going on numerous data collection trips under different environmental settings to attempt to cover all conditions under which the object of interest can be found in, data augmentation can be used to increase the amount of data. Data augmentation is a process of generating new data samples by transforming them in some way, there are various ways to do this such as random cropping, rotation, radiation transformation, noise injection, flipping, and translation (Wang et al., 2020) (Shorten & Khoshgoftaar, 2019). Not all these different augmentation methods will work well for training in all situations, it is important to know the kinds of data augmentation methods that will be appropriate for this study. (Wang et al., 2020) did an extensive study into augmentation methods that may improve training of crack detection data samples in concrete settings, they found that rotation was the best out of nine methods for improving the performance of the trained model. One study (Taylor & Nitschke, 2017) categorised the augmentation methods into geometric methods, which altered the geometry of the image my changing the location of the pixels in space, and photometric methods which changed the color channels of red, green, and blue (RGB) to new pixel values based on some pre-determined heuristics. They found that cropping had the best improvement in the performance of the model in classification accuracy. Following the recommendation of literature, rotation, and cropping were used for data augmentation in this study as they showed good results in related works.

3.3 EDGE DETECTION

One of the more common procedures for carrying out edge detection is explained in (Ziou & Tabbone, 1998) is the canny edge detector. The researchers outline three broad operations in edge detection starting with differentiation, smoothing, and labelling. Differentiation is about defining the desired features or edges of a feature that should be detected, smoothing is about denoising, were other features in the image that are not of interest have their prominence reduced so that their edges will not be identified later on. Finally, labeling consists of the isolation of edges and increasing the edge signal to noise ratio by suppressing unwanted edges. Figure 15 below outlines how these three-step processes was understood and implemented in the currently study.

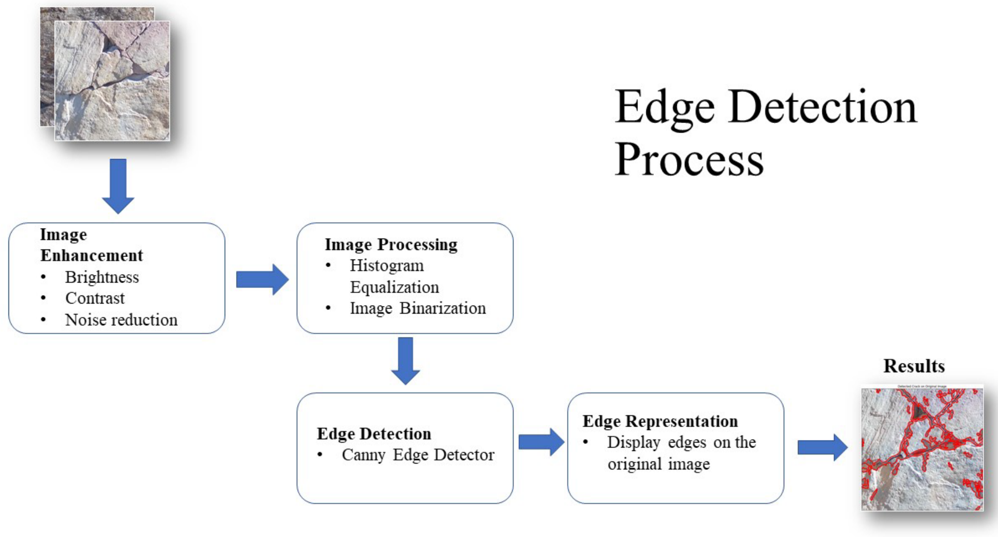

Figure 15 Edge detection process

The main aim of image enhancement is to improve the quality of an image to give a better input for downstream image processing (Janani et al., 2015). There are several techniques of image enhancement which can be categorised into spatial domain, were by the operation is implemented at the pixel level of the image, and frequency domain methods which are applied on the Fourier transform of the image. A lot of research (Igbinosa Ireyuwa, 2013)(Shrivakshan & Chandrasekar, 2012)(Ziou & Tabbone, 1998) and real time solutions around edge detection rely more on spatial domain methods due to ease of interpretation, simplicity, and low complexity (Janani et al., 2015). As seen in Figure 15 above, the methods employed were brightness and contrast adjustment, coupled with noise reduction. Noise reduction was achieved using the gaussian filter method. The inputs to this method include the image to be filtered, the kernel size in width and height, and a sigma value for the standard deviation. The most effective sigma value for the images in this study was σ = 2, and the OpenCV function for this operation can calculate the kernel size automatically from the sigma.

After noise reduction, the image is transformed to grayscale which allows for more image processing techniques to be applied to it. Histogram equalization is another method of adjusting image contrast, it involves transforming the intensity values of the image by stretching the intensity range across more pixels (Huamán, 2023b). The steps described above have all be aimed at trying to isolate the wanted edges in the image, once that is completed the image can be binarized which makes it easy for edges to be calculated. To binarize an image, you set a particular threshold value and if the pixel value is above this value it will change to some maximum value and below that threshold it turns to zero. The equation below defines this, dst is the destination image, src is the source image, thresh represent the threshold value, and maxVal is the value to which all pixel above the threshold will be set (Huamán, 2023a).

$$dst(x,y) = \begin{cases} maxVal & if\ src(x,y) > thresh \\ 0 & otherwise \end{cases} \tag{7}$$

Once the aforementioned preparation steps have been completed, the edge detection process can commence. The Canny edge detection method is highly effective among various edge detection methods. The Canny edge detection method, developed by John Canny in 1986, was designed with three primary objectives. A reliable edge detection method that accurately identifies edges without any omissions. Accurate edge localization within specific pixels. To achieve a high response rate, it is important to accurately identify multiple edge pixels in cases where a single edge is present. The implementation of the Canny edge detector involves applying a Gaussian filter to the image for noise reduction, followed by determining the gradient magnitude and direction. If the magnitude of the gradient of a pixel is greater than the magnitudes of its two neighboring pixels in the direction of the gradient, classify the pixel as an edge. Otherwise, classify the pixel as the background (Igbinosa Ireyuwa, 2013).

To display the edges on the original image and make other possible calculations such as length and area a FindContours command is used to filter out and superimpose some of the representative edges found.

3.4 MODEL DESIGN

In earlier chapters, the intricacies of CNNs were explained. When tasked with devising a model, it is paramount to understand the complexities that govern its structure. Models, in a broader sense, encapsulate the entire machinery responsible for transforming data into insightful predictions or decisions. Within this framework, neural networks stand out as an exemplary subset, mimicking the intricate connectivity of the human brain. As we delve into the specifics, the focus on CNNs emerges, especially for tasks involving grid-like data, such as images. In the following sections, we will explore the development of a particularly influential CNN architecture, the UNet, and shed light on the crucial elements shaping its design.

3.4.1 U-Net ARCHITECTURE

The U-Net architecture was developed by (Ronneberger et al., 2015) as an innovative component in the difficult task of image segmentation of biomedical images. As its name suggests, the U-Net design exhibits a unique U-shaped structure, depicted in Figure 16 encompassing a contracting path, also known as an encoder, and an expanded path, also known as a decoder.

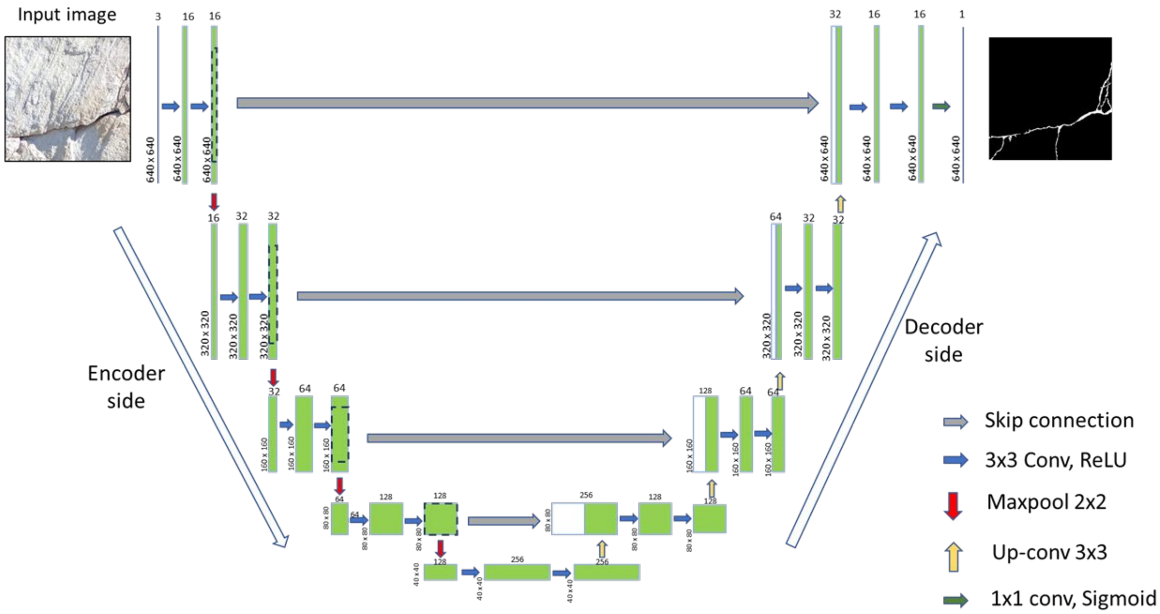

Figure 16 U-Net model(Ronneberger et al., 2015)

The encoder component of a U-Net architecture assumes the crucial role of capturing and encoding the salient features of the input image across various hierarchical levels of abstraction. The aforementioned process assumes a pivotal role in the extraction of hierarchical representations from the given input, thereby advancing from granular low-level particulars to more abstract high-level semantics. This process of contraction is characterized by the utilization of input layers, convolutional layers, downsampling, dropouts, and ReLU activation functions, which facilitate the acquisition of contextual information. The input layer is of size 640 X 640 pixels and 3 color channels, which dictates the size of the input images, this choice of a 640 X 640 input layer aims to balance computational efficiency with the preservation of spatial details of the image. As the input progresses along the encoder convolutional blocks, the spatial dimensions gradually decrease, while simultaneously extracting intricate high-level information. Each of these convolutional blocks consists of a (3, 3) convolutional layers, ReLU activation, and same padding, dropout layer with a progressive dropout amount, and maxpooling filter of size (2, 2).

The choices made in the encoder side help with a number of things, capturing both intricate low-level features and higher-level semantics in the case of convolutional layers, the dropout layer introduces regularization, preventing overfitting and fostering the learning of more robust features which will help the model with preventing excessive co-adaptation of neurons and maintaining the model's capacity to perform when introduced to unseen data. The repeated application of convolutional layers and max-pooling contributes to the hierarchical abstraction of features, culminating in a bottleneck block that encapsulates abstract representations. The expanding pathway aims to restore spatial information through the utilization of transposed convolution and ReLU-activated convolutional layers of size (2, 2). Significantly, skip connections are intricately integrated, establishing connections between equivalent levels of the contracting and expanding pathways. The strategic connectedness present in U-Net allows for the retention of intricate spatial information and enhances accurate localization, which has been a significant factor contributing to the success of this model in other studies. The selection of (3, 3) convolutional layers in the decoder, accompanied by dropout and additional convolutional layers, reflects a deliberate effort to refine and augment feature representations. The ultimate addition is a 1x1 convolutional layer that incorporates a sigmoid activation function, resulting in the generation of a pixel-wise binary segmentation mask.

The selection and tweaking of hyperparameters play a crucial role in determining the performance of the model. Hyperparameters need researchers to make well-informed decisions in order to maximize performance. In the domain of U-Net, thorough calibration is required for critical hyperparameters such as the number of filters, learning rate, and batch size. The contracting and expanding pathways, which include the use of convolutional and transposed convolutional layers, require careful changes in order to achieve an appropriate trade-off between retaining information and ensuring computational efficiency. Regularization strategies, such as dropout, serve as a defense mechanism against overfitting, hence enhancing the model's capacity to generalize to new and unknown data. The selection of a loss function, cross-entropy in the case of this study, and an optimizer, such as Adam optimizer, plays a crucial role in determining the efficacy of model training. Conducting a thorough assessment on a separate test dataset offers valuable insights into the practical performance of the model, leading to repeated adjustments of hyperparameters in order to strike a well-balanced equilibrium between computational efficiency and prediction accuracy. Some of the code used to develop this model was adapted from (Bhattiprolu, 2023).

3.4.2 PRE-TRAINED MODEL

Training a machine learning model is a resource intensive and time-consuming task that usually requires a large amount of data and in the area of image segmentation, every pixel in all those images have to be annotated in the pre-processing stage which is a massive time commitment. To get around these issues steps such as data augmentation (Wang et al., 2020) to increase dataset, and using simpler training models to reduce computational demands may be used. Another popular option is to use pre-trained models for to tackle the issue at hand. A pre-trained model refers to a neural network model that has undergone extensive training on a substantial dataset, with the aim of accomplishing a particular task. Subsequently, this model is preserved or disseminated for the purpose of subsequent utilization in a distinct, albeit interconnected, task (Iglovikov & Shvets, 2018). The fundamental concept underpinning pre-training is to harness the acquired knowledge derived from successfully addressing a particular task, known as the pre-training task, and subsequently employ it to tackle a closely related task, referred to as the target task. This approach proves to be particularly advantageous in scenarios where the target task exhibits a scarcity of annotated data. This is owing to the fact that the pre-trained model has already assimilated valuable features from the extensive corpus of data employed during its initial training phase.

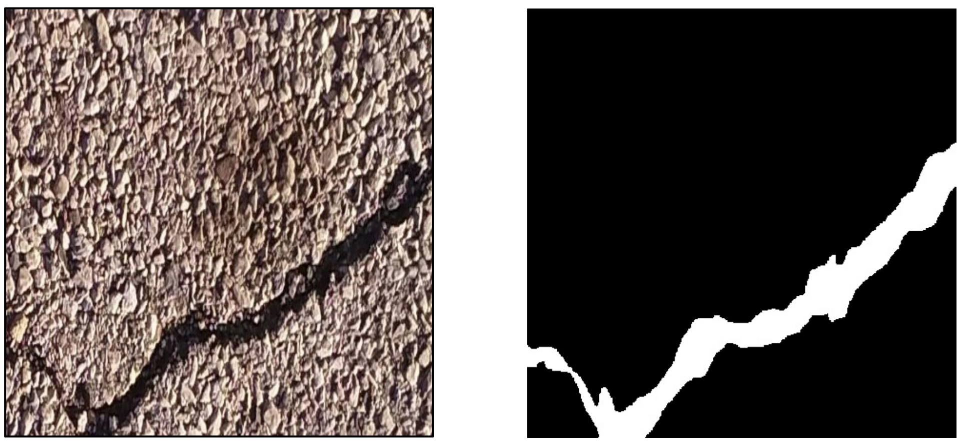

Figure 17 Example of image and annotation mask from (Liu et al., 2019). *dataset*

In this study a U-Net model was pre-trained on a 5 000 image dataset put together by (Liu et al., 2019). The dataset is made of asphalt and concrete crack images as seen in Figure 17 above, it was put together from smaller datasets and new images captured by the researchers above. After training, the learned weights and architecture of the model are saved and fine-tuning is conducted. Fine-tuning is were by specific components of the model a retrained on the new dataset which allows the model to adapt to the specific features and patterns of the new task.

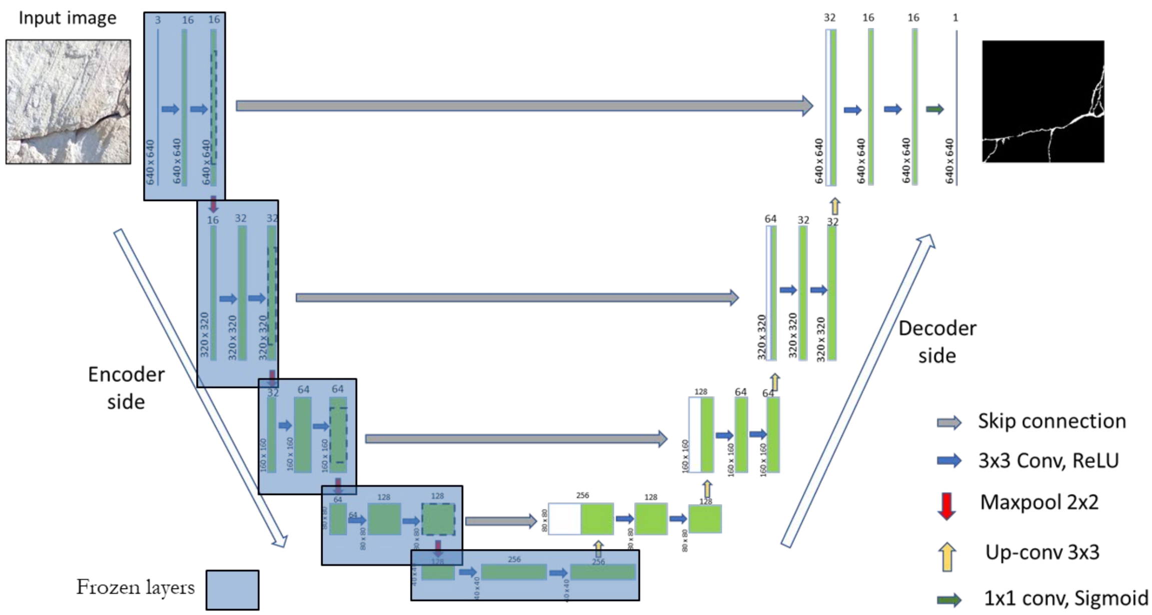

Figure 18 The encoder side of the U-Net were frozen after the initial training

As the model under goes training, the encoder side of the model will be frozen, shown in Figure 18, so that those previously trainable parameters become non-trainable parameters as they will have the trained weights from pretraining. The decoder side of the model can be approached in different ways, training can be continued on the weights that have been previously trained or trained can be done on completely new weights that have not undergone any training at all.

CHAPTER 4 : **RESULTS AND DISCUSSION**

This chapter presents the outcomes of a comprehensive investigation into crack and fracture detection on mine highwalls, employing a comparative analysis of three distinct methodologies: traditional edge detection techniques, a U-Net model constructed from scratch, and a U-Net model pretrained on relevant datasets. Traditional edge detection algorithms offer a baseline for comparison, representing conventional methods widely employed in computer vision studies. The U-Net architecture, a convolutional neural network known for its proficiency in semantic segmentation tasks, is explored both from a ground-up construction perspective and as a pretrained model leveraging transfer learning and fine-tuning.

4.1 EDGE DETECTION

The steps followed for edge detection were outlined in the previous chapter. Figure 19 below shows the outcome of the first step of image enhancement in which the image underwent brightness and contrast adjustment, and a gaussian filter applied to reduce noise. These first steps allowed for the background features of the image to be minimized so that they are not widely detected when edge detection methods are applied to them. When these background features of images are minimized, this in itself maximizes the appearance of the foreground features of interest. Following the image enhancement process is histogram equalization and binarization, histogram equalization did well to highlight the remaining features in the image at this stage of processing, but this presented a downside as seen on Figure 20 were the histogram equalization method was too sensitive to elements in the image that are classified as background and should not be detected.

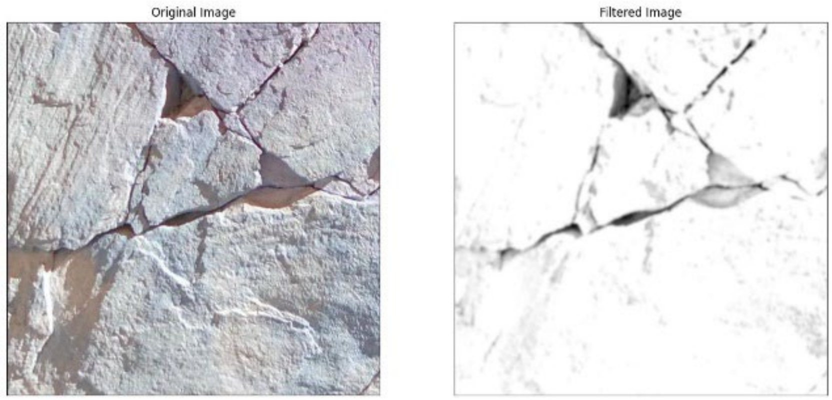

Figure 19 Filtered image went through brightness and contrast adjustment, gaussian filtering, and then turned to grayscale.

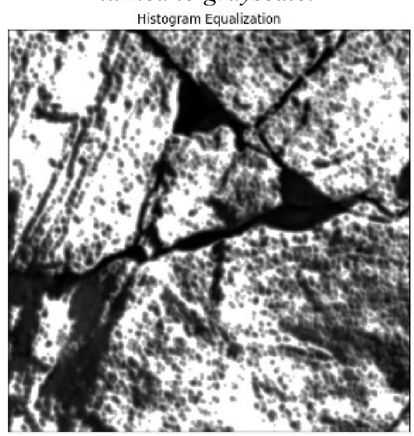

Figure 20 Histogram Equalization

With the sensitivity of histogram equalization, binarization became a more viable method to proceed with. A number of techniques were tested in accordance with the literature (Huamán, 2023a) these include simple thresholding, adaptive thresholding, and the Otsu's binarization seen in Figure 21. Both adaptive thresholding and Otsu's binarization attempt to account for all the features in the image, adaptive thresholding for example uses a local thresholding type of process by determining the maximum pixel values in user defined search area and elevating those pixels with higher pixel values. Otsu's binarization uses a similar global thresholding process used by the simple thresholding method, the difference is that it selects its own thresholding limit by considering all pixel values which leads it to elevate the features represented by those pixels. The simple thresholding method was the most reliable of the three methods, but adaptive thresholding was also better to use for certain images. Simple thresholding is more intuitive in this case as it is easier to control the degree of sensitivity of the method.

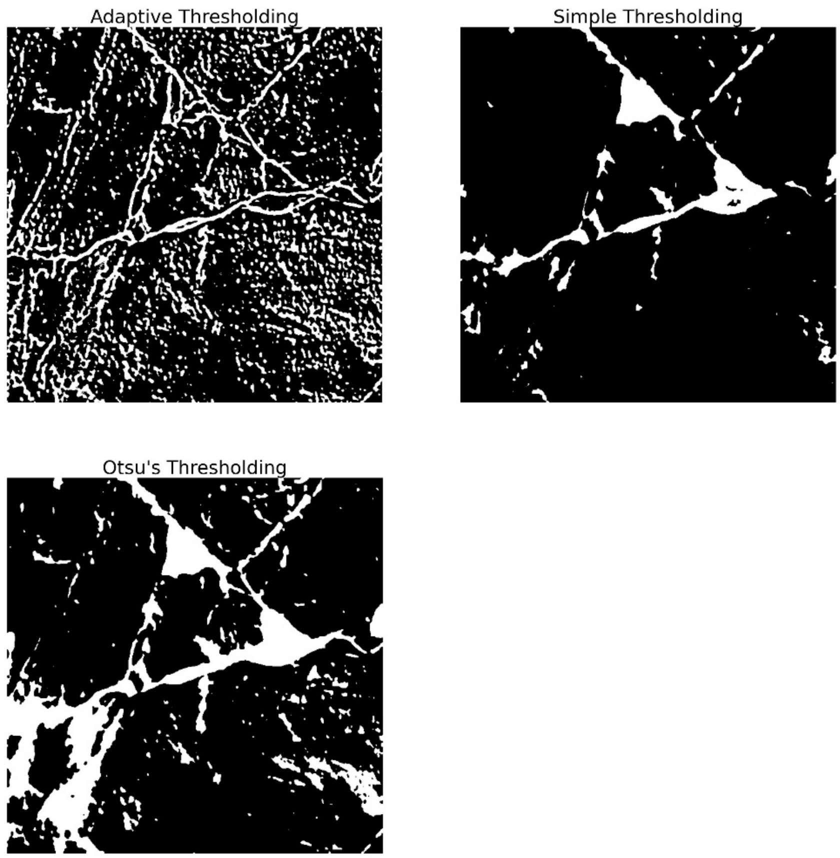

Figure 21 Performance of different binarization methods

After thresholding, edge detection is applied to isolate exactly were the fractures and cracks start and end. The canny edge detector is applied to the binarized images and if the prior steps are followed, detecting the edges will be fairly simplified. After detecting the edges, they can now be superimposed on the original image to see how well they align with the cracks or fractures observed. Figure 22 shows the final output of edge detection.

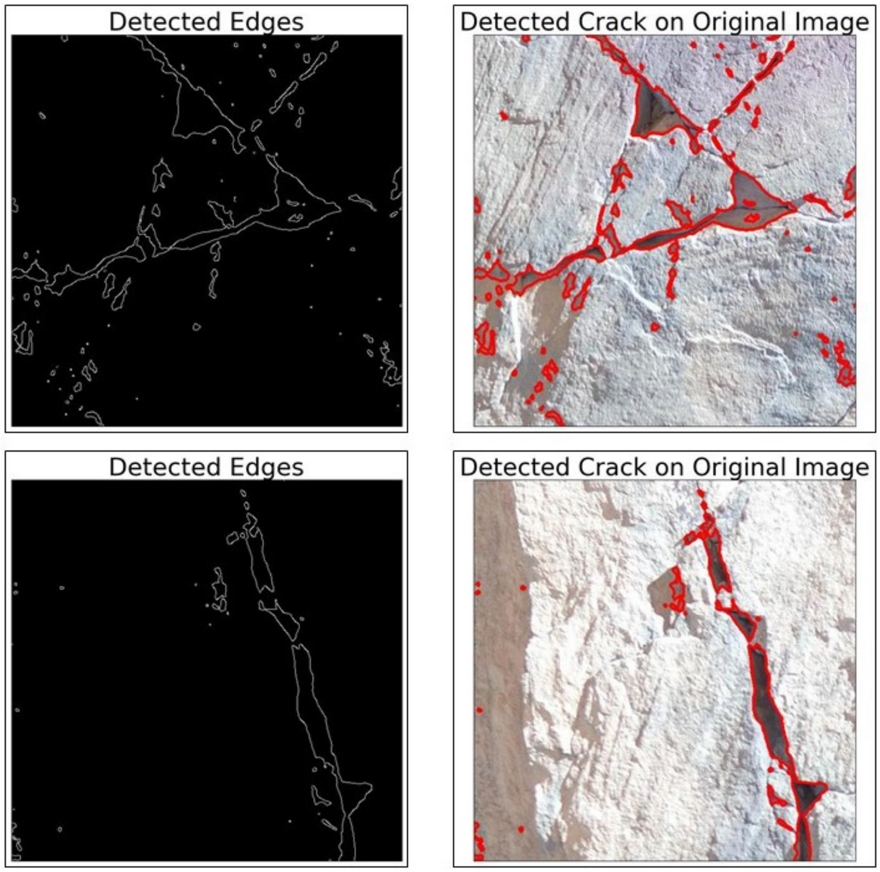

Figure 22 Detected edges from the edge detection procedure and the edges plotted on the original images

4.2 U-Net MODEL

The U-Net model employed for this work was explained in the previous chapter and Figure 16 outlines the structure of the fully convolutional model. The extensive TensorFlow and Keras libraries were used to prepare the python code, these libraries contain a number of functions and classes related to machine learning that were used to develop the python code used in this study (*TensorFlow*, 2023). Another python library used was the OpenCV library which is a computer vision library, was essential in importing the image data from the computer and performing several manipulations to that image data so that it can be ran through the model during training.

4.2.1 Data Pre-Processing

To prepare the image data for training the model, several pre-processing steps were followed such as image tiling, augmentation, and normalization. The images collected during data collection had large dimensions at about 4000 x 3000 pixels, a decision was made to reduce the size of these images before using them in the model. Convolutional neural networks can handle large image sizes, but literature suggests that in most instances this leads to long training periods and high computational demands. A couple of methods where looked at to achieve this desired input size, resizing the images or cropping them. Resizing the images was considered first, the issue that came up here was that scaling an image by such a large amount results in pixelation and loss of important image details. This is somewhat counterproductive for a ML framework because for the model to be able to make accurate predictions, it has to be able to learn from clear features on the images. Image cropping is an alternative method, it serves two purposes in that it produces the image size desired without compromising on image resolution and is an augmentation method as well which helps increase size of the dataset. Figure 23 below shows the difference between these methods and it is apparent that the cropped image is better for showing the fractures that this thesis work is attempting to identify.

The next step was image augmentation. Cropping was already done to get the desired size images for training, image flipping, and image rotation were the other two geometric augmentation methods used in this study, coupled with brightness adjustment as a photometric method (Taylor & Nitschke, 2017). These methods are widely used for image augmentation due to their computational efficiency.

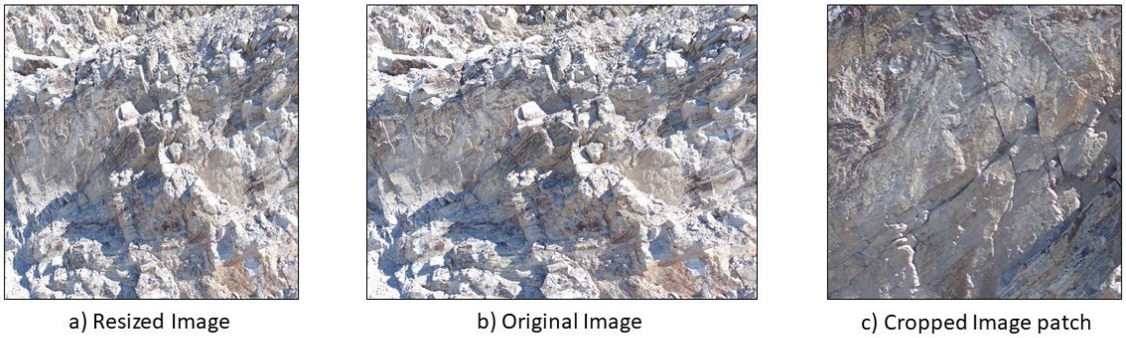

Figure 23 Comparison between an original image, its resized image on the left and a cropped patch from the image

4.2.2 MODEL TRAINING

Two training iterations of this model were conducted. In the first iteration there were only 100 annotated images used. The data was randomly separated into two categories, 80% portioned to the training set and 20% to the testing set. To train the model, several model hyperparameters have to be selected. Table 7 below outlines the selected hyperparameters for the initial training process, most of the selection decision were advised by research done in adjacent industries like construction.

Table 7 Hyperparameters selected for model training

Hyperparameter	**Value**
Input Size	(640, 640, 3)
Activation Function	ReLU
Dropout	0.1 -0.3
Pooling	MaxPooling2D
Upsampling	conv2d_transpose
Loss Function	Binary Crossentropy
Optimizer	Adam
Learning Rate	0.001
Batch Size	5
# of Epochs	30
Early Stopping	Validation loss, patience=4 epochs

Figure 24 and Figure 25 below outline the accuracy and losses tracked during the model training period.

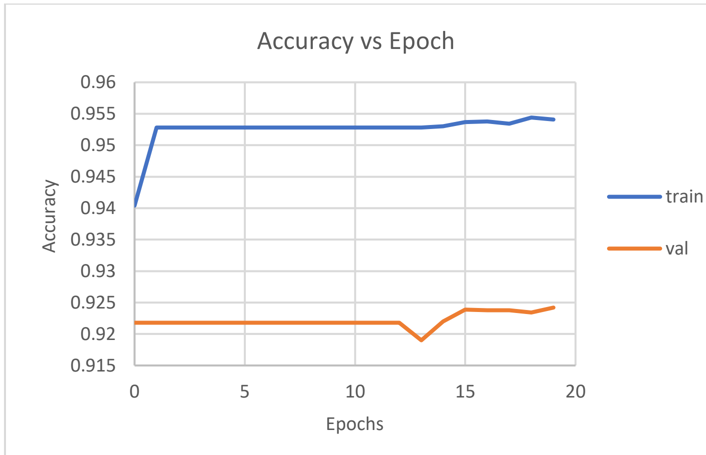

Figure 24 Training accuracy of U-Net trained with 100 images

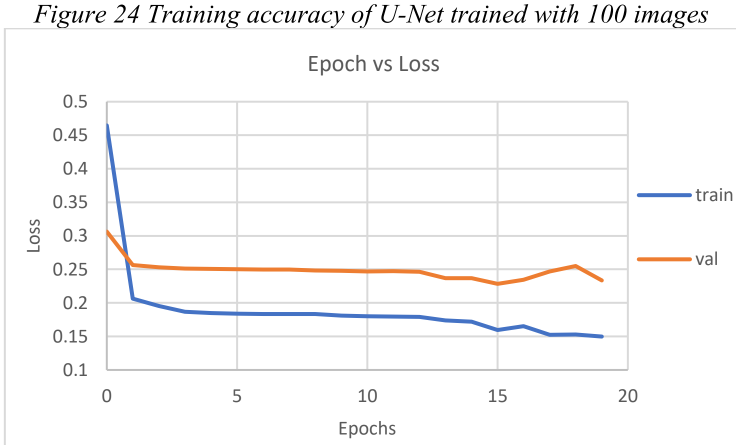

Figure 25 Training and validation loss of U-Net trained on 100 images

The model trained to only 20 epochs due to the early stopping protocol that was set to track validation loss and end the training if the validation loss does not show improvement for 4 epochs. The U-Net model demonstrates exceptionally high accuracy in both testing and training data, according to literature this may be a common trait when training on imbalanced data. A discernible performance gap is observed between the training and validation set, with the losses converges at 0.22 and 0.14 respectively. These figures may suggest that the model has successfully learned the inherent features of the training set, but its generalization capability to unseen data could be further improved. The outcomes from this training period suggests that further investigation into the ability of the model to generalize is needed, and a more improved data size as well. The second training iteration consisted of the same U-Net architecture model, but it included data augmentated using augmentation methods such as rotation, brightness adjustment, cropping, saturation, and flipping which increased the dataset to 1000 images and a few hyperparameters where adjusted as well. The batch size was increased to 15 and the learning rate was changed to 0.0015 with epoch number of 40.

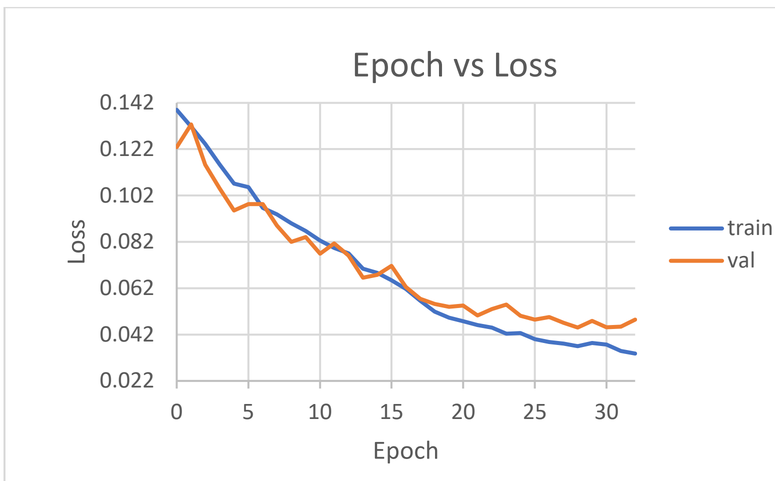

Figure 26 Training iteration with 1000 images

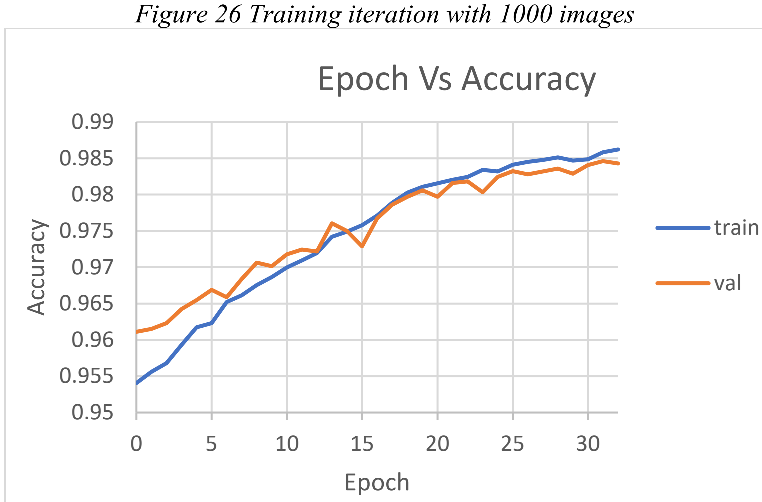

Figure 27 Training accuracy of U-Net model trained with 1000 images

Figure 26 and Figure 27 above shows how the training progressed. The U-Net model manifested some convergence during the training phase. This efficiency extends to the validation set, where the loss stabilizes at a slightly higher but comparable value. The accuracy metrics in both the training iterations explained above show a high proficiency, which is not very surprising in image segmentation of this nature where the background is so largely represented in many images. Further model evaluation methods will need to be looked at to determine how well the model may be performing.

4.3 PRE-TRAINED U-Net MODEL

Another option that was explored was using a pre-trained U-Net model as a base for accomplishing the objectives of this research. There are a number of reasons to use a pre-trained model, for the purposes of this study there were three main reasons that it was considered; data efficiency, time and resource savings, and adaptation to a new domain. Under data efficiency, using a pretrained model allows researchers to work with a smaller dataset because the pre-trained model has already learned from a large dataset so if there are any data acquisition or pre-processing challenges a pre-trained model will help bridge that gap. As for time and resource, Training deep neural networks, especially U-Net models with many parameters, can be computationally expensive. By starting with a pre-trained model, you can significantly reduce the training time and computational resources needed for convergence. Lastly, if the dataset of the pre-trained model is closely related to the current project dataset, similar types of images for example, the pre-trained model can be effective in adapting to the target requirements, even if the tasks differ slightly.

The model used for this pretraining is the same U-Net model architecture described above. The dataset was also touched on in the previous chapter, Figure 17 show an example of the dataset. The 5000 images had dimensions of 448 x 448 pixel, thus in the pre-processing stage they were upsized to 640 x 640 pixels and this was done to keep these images consistent with the images in the project dataset.

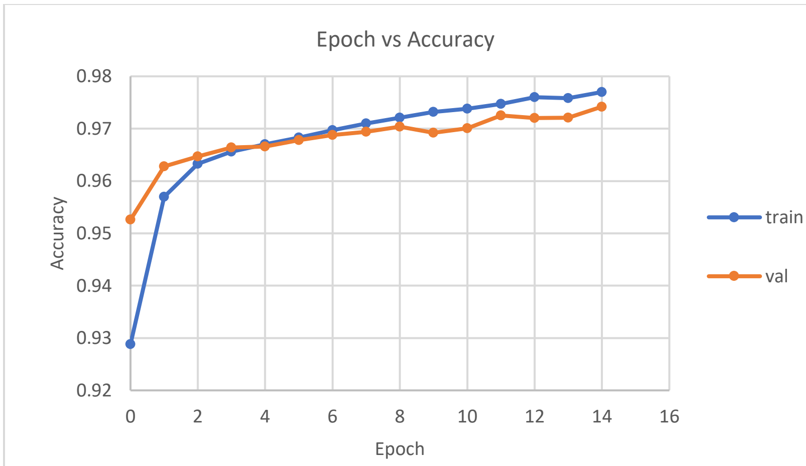

Figure 28 Accuracy for the pretrained model training iteration

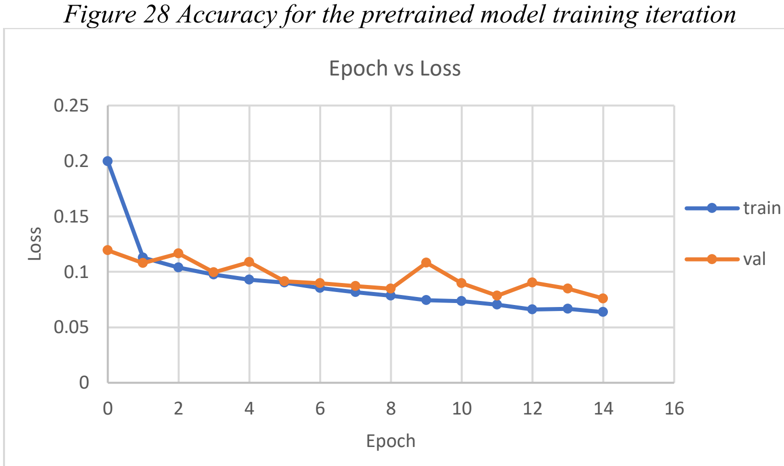

Figure 29 Loss for the pretrained model training iteration

The pretrained model was then trained on the 1000 images in the dataset of this project, the training setup consisted of 15 epochs, batch size of 15, and a learning rate of 0.001. Figure 28 and Figure 29 above shows how the training progressed, the accuracy of both the training and validation were trending up around 97%. The loss also displayed some convergence as it was trending down for both training and validation which indicates that the model might be generalizing well to unseen data, this insight was further seen when the model was tested on 220 images it had not seen before and scored an accuracy of 97%, which is consistent with training and validation, and a loss of 0.0835 which is slightly higher, but close to the training loss.

4.4 MODEL EVALUATIONS

To keep the performance evaluation similar across the board, four basic evaluation metrics were utilized for the different segmentation methods in this study and these are precision, recall, F1 score, and intersection over union (IoU). The relevance of these methods was considered under section 2.6.3 of this write up, in summary they are concerned with how well the segmentation method is able to classify each and every pixel of the image in the testing data into a fracture pixel or no fracture pixel and matches this to the segmentation mask/GroundTruth. To calculate the metrics above a confusion matrix has to be determined first, this matrix contains the true positive (TP), true negatives (TN), false positive (FP), and false negative (FN) values obtained from comparing the predicted segmentation mask with the GroundTruth or actual segmentation masked obtained from human annotation. The configuration of a confusion matrix is seen in Table 8.

Table 8 Pixels in each image are separated into the different categories shown

	GroundTruth	
Prediction	No Facture (0)	Fracture (1)
No Fracture (0)	TN	FN
Fracture (1)	FP	TP

The mathematical equations that define the metrics above can also be found in section 2.6.3. The TensorFlow Keras library was used to calculate the confusion matrix and from that the values of precision, recall, F1 score and IoU were calculated. Table 9 below shows the metrics calculated and thus the numerical performance of the different iterations and methods investigated in this research. U-Net_100 was the initial iteration of just 100 annotated images and segmentation masks. U-Net_1000 has the same model architecture as U-Net_100, the only difference was that image augmentation was performed on the images. The pretrained_U-Net also has a similar architecture as the first two models, the encoder side of the U-Net model was first trained on a different but similar database, different hyperparameters were also explored for these models as discussed in section 4.2.2 above.

Table 9 Training iterations and their respective scores on various ML metrics

Methods	Pr	Re	F1	IoU
U-Net_100	0.7014	0.1399	0.2206	0.5397
U-Net_1000	0.7733	0.6645	0.6993	0.7706
Pretrained_U-Net	0.7213	0.4878	0.5597	0.6928
Edge detection and Thresholding	0.6968	0.7329	0.7072	0.7504

In addition to the numerical metrics compared above, it is important to study the visual outcome in the form of a segmentation mask generated by these models. This is an important step because a visual inspection of the segmentation masks can give some valuable insight on the areas of the image that the U-Net model may be struggling or excelling at segmenting, insight that can be used to improve the model in the next training iterations. Figure 30 shows these visual outputs and it is clear that as the metrics above depict, the U-Net_1000 model trained on 1000 images and the pretrained_U-Net model have a superior performance to the U-Net_100 model trained on 100 images.

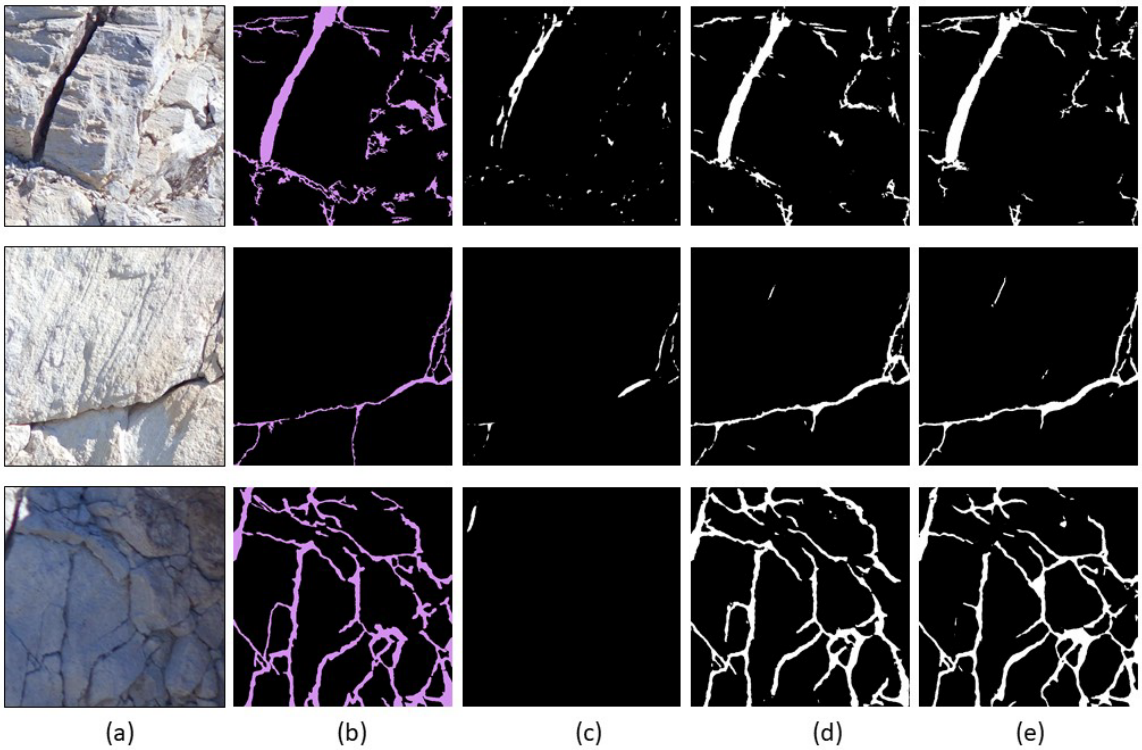

*Figure 30 Comparison of predicted results among various methods and iterations on the fracture dataset. **(a)** original image, **(b)** GroundTruth, **(c)** U-Net_100, **(d)** pretrained_U-Net, **(e)** U-Net_1000*

4.5 DISCUSSION

The pursuit of an effective crack and fracture segmentation methodology on mine highwalls represents a significant stride toward enhancing safety and structural assessments in the harsh mining environment. In this study, a multi-faceted approach was employed to attempt to integrating U-Net models, edge detection and thresholding techniques to unravel the complexities of detecting major and minor fractures along mine highwalls. The investigation spans several iterations of the U-Net model training, coupled with the more traditional edge detection, each marked by distinct training strategies and data configurations. This discussion meticulously dissects the comparative performance of these iterations, addressing nuances, challenges, and the overarching implications for the research question: Can photogrammetry and machine learning be employed to detect major and some minor cracks on mine highwalls?

The U-Net models, constituting the backbone of the machine learning approach, underwent iterative refinement. The first iteration, trained on a modest dataset of 100 images without augmentation, revealed limitations in performance, indicative of the model's struggle to capture the complexity of highwall fracture patterns and the diverse nature of the image background. The model still demonstrated high levels of accuracy during training at 95.41%, with training loss at a low level. Accuracy can be a misleading metric in assessing image segmentation models, especially considering the data used in this study were the majority of the pixels in any one image belong to one class, this can inflate the accuracy so it is important to consider other metrics such as IoU, on which this first iteration performed at 53.97%. The second iteration was deployed on an expanded dataset of 1000 augmented images and a nuanced adjustment of the learning rate from 0.001 to 0.0015. This model setup emerged as the top performer across various evaluation metrics, which underscores the critical role of data diversity and volume in enhancing the U-Net model's segmentation capabilities. This model set achieved the highest Pr, IoU, and a comparable F1 score when put up against the other training iterations as seen on Table 9 above.

The third iteration, leveraging a pre-trained U-Net model on asphalt and concrete crack images, demonstrated substantial competence, securing the second-best performance.

Freezing the encoder layers during training on mine highwall fracture images allowed the model to transfer relevant features from the source domain. This finding accentuates the potential of transfer learning, especially when pre-training data closely aligns with the target domain. The pretrained model showed great performance in the IoU measure, but less so for precision, recall, and F1 score. This indicates that the model may be achieving high spatial accuracy by correctly predicting the presence and location of features, but struggling with the exact class or intricacies of the boundaries. This may be caused by class imbalance in the dataset, this means that one class may be over represented in the images provided.

In parallel to the U-Net model, an edge detection and thresholding workflow was developed as a means of comparison between more traditional methods of detection in computer vision and newer deep learning approaches. The performance of edge detection closely mirrored that of the U-Net model trained on 1000 images, suggesting that, in certain contexts, conventional methods can rival the efficacy of machine learning models. To achieve these kinds of results from edge detection does require a significant amount of work by the research as compared to a deep learning approach to the problem. Due to the differences in the make-up of images in terms of pixel values, the edge detection workflow such as the blurring effect, image enhancement and thresholding would have would have to be altered slightly to suit the image currently being handled. However, this finding underscores the importance of evaluating the trade-offs between computational complexity and performance, especially in resource-constrained environments.

CHAPTER 5 : **CONCLUSION**

A U-Net model was developed for this thesis work to identify and segment fractures on open pit mine highwalls as a means to augment the current practice of human visual inspections. The U-Net model was trained on data obtained from an open pit aggregates mine located in Storey county just outside Reno Nevada. Three different scenarios where setup for training the model and these configurations were centered around the availability of data, the first configuration was training the model on a modest dataset of 100 images, the second configuration was on a dataset using the same model architecture, but with a dataset of 1000 images contain original and augmented images. The third configuration relied on the benefits of transfer learning, were by a machine learning or deep learning model is trained on a different, but related dataset, in this case images showing cracks on concrete and asphalt. The pretrained model is repurposed to train on the relevant dataset using the knowledge gained from prior training to assist in better learning the features of the current data set. In addition to these 3 different configurations, a traditional edge detection method was used to serve as a comparison between the newer methods of deep learning and more classical methods of pixel wise detection.

The data collection was one of the more important parts of this thesis work. The use of UAVs has become ubiquitous in the mining industry which makes the collection of image data around the mine much easier than in the past. Challenges still exist, most UAVs used for surveying do not require a high level of accuracy because the data is mainly used for volume calculation and measurements, and in the mining industry were tens of thousands of tons are being excavated a day, there is low requirement for a high level of detail. But for the kind of work done for this research it was important to collect fairly good image data so that the relevant features can be easily extracted by a deep learning model. To achieve this a specific setup for the drone flights was setup using the UgCS drone flight application, this entailed a simple setup of surveying vertical surface with the camera at a 90-degree angle to the surface, which proved to be the best set up for collecting the data needed for this work.

After data was collected, pre-processing began. This step is an important one as well, and it takes some time to complete, but it was very beneficial to take more time preparing the data because it made the training process that much easier. Data annotation was a key element to the whole thesis work, this is because for the deep learning model to work it needs images and their respective segmentation masks so that it knows which features belong to which category. This step was one of the main challenges encountered in this thesis work, the images in the dataset were somewhat complex and making errors at the begging stages of annotation was part of the process, which caused some delays.

Once pre-processing was complete the model was coded and training began. The U-Net model was first introduced by (Ronneberger et al., 2015) for use in the biomedical field. It was later widely adopted for many areas were computer vision is applicable. This model architecture was modified in accordance with the currently industry uses similar to segmentation of fractures. The main challenge when it came to training was availability of computing resources, some of the training iterations took some time, especially with the pretrained model due to the size of the dataset.

The goal of this thesis work was to characterize the possible causes of highwall damage in the normal process of mining, use drone photogrammetry in combination with deep learning techniques to identify cracks and fractures on open pit highwalls. Firstly, from the literature reviewed during this project, it is clear that damage found on mining highwalls is usually caused by a combination of the in-situ conditions such as the rock mass properties, geologic structures (faults, shear zones, and joints sets), pore pressure due to groundwater presence, and blasting practices that results with too much energy from the blast engaging with the remaining highwall through ground vibrations and backbreak events. The combination of all these elements are why geotechnical monitoring is such an important part of the safety practices in the mining environment, and why improving those monitoring methods is an important undertaking.

Secondly, it was shown through the data collection stage that the use of UAVs or drones is very useful in the mining industry and that utility was the backbone of this research work. Mine highwalls are hard to reach places, most open pit mines are 100s of feet deep and access to most of the highwall work capturing data needed for this thesis work would not be possible without the advanced drone technology in the market today. Lastly, this work has shown how the use of artificial intelligence, deep learning in particular is such a pivotal turn in the mining industry. The U-Net model used in this work showed a lot of potential to be a practical tool in the mining industry, the model was able to identify a lot of the cracks and fractures in the test image provided. The IoU scores the model attained showed that the model does well to correctly locate and delineate the features in the image. That said, with the availability of a large annotated dataset, much better performance can come to be expected from this model.

5.1 POTENTIAL FUTURE WORK

The work that has been done in this thesis has the potential to be extended in many ways. The National Institute of Occupational Health and Safety, which sponsored the research grant under which this work was funded is always looking for new ideas to make the mining industry safer and productive.

5.1.1 INCORPORATION OF MORE DATA

Collecting relevant data from mining companies is a difficult task, but one that should be done continuously to amass a large enough dataset to keep on hand. Deep learning models work very well when they have a large dataset to train on and mine operations generate this data on a daily bases, with a larger dataset the model used in this current study can be tested further to see if any improvements can be made its performance. Diversifying the dataset is another benefit of more data collection, there are a variety of rock types at different alteration stages that may present differently at a pixel level in an image, and including those diverse imagery in the training set, might help the model generalize better.

5.1.2 TESTING DIFFERENT MODEL ARCHITECTURES

The area of artificial intelligence is always growing, new and advanced learning models are being developed all the time and it would be beneficial to test out newer segmentation models as they are developed or more interestingly to merge existing models to see if any performance can be gained from that. A deep learning models such as the encoder decoder model, which is very similar to the U-Net model, is very good at extracting features from data and could possibly be measured with a U-Net model to improve the way it learns features from images before producing a segmentation mask.

5.1.3 GEOLOGIC STRUCTURE CHARACTERIZATION

As I mentioned in previous chapters, some of the in-situ ground conditions that can be found in mining areas include faults and joint sets. Currently drilling campaigns are conducted during exploration, before mining starts, and from the data gathered from this drilling faults and joints can be modelled. More can be done in this area of characterizing faults because as mining progresses, those faults and joints in the ground can also be observed as fractures on mine highwalls and they can be identified through the use of the imagery and deep learning models. But to go one step further, there may be a possibility to use the images collected to make a 3D representation of the highwall and using similar deep learning models, identify not just the fractures, but the direction the fracture or fault in this case, might be extending back into the highwall known as the strike.

5.1.4 CONNECTING FRACTURE DENSITY TO BLASTING OPERATIONS

The highwall condition of a mining operation is influenced by the in-situ ground conditions, coupled with blasting outcomes. There isn't much that can be done about the ground conditions, mine operators have to work within those constraints. However, this research can be couple with descriptive scales of blasting outcomes such as the one outlined in Table 1, to rank the highwall condition and then use machine learning and deep learning algorithms to connect the condition of the highwall with the drill and blasting parameters (burden, spacing, stemming etc.) selected for that area to see the degree of correlation and possibly use this to inform on which parameters are best suited for that mining area.

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DATA AND SOURCE CODES

The data and codes used in this thesis work can be found at the GitHub repository at the link below. Please reference this thesis work if you intend to use any of that data.

GitHub: Images and code for training semantic segmentation model