University of Nevada, Reno

Detection and Monitoring of Tailings Dam Surface Erosion Using UAV and Machine Learning

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

By:

Florida Febriana Udam Nasategay

Javad Sattarvand, Ph.D. / Thesis Advisor

August 2020

THE GRADUATE SCHOOL

We recommend that the dissertation
prepared under our supervision by

FLORIDA F NASATEGAY

entitled

Detection and Monitoring of Tailings Dam Surface Erosion Using UAV and Machine Learning

be accepted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE

Javad Sattarvand. Ph.D.
Advisor

Masoud Zare-Naghadehi, Ph.D.
Co-advisor

Ebrahim Emami Gohari, Ph.D.
Committee Member

Behrooz Abbasi, Ph.D.
Committee Member

Poria Fajri, Ph.D.
Graduate School Representative

David W. Zeh, Ph.D., Dean
Graduate School

August, 2020

ABSTRACT

The recent failure that occurred in Burmadinho had yet added the list of tailings dam failure within the mining industry. The industry is currently in search of a better way to avoid them from happening again in the future. Most of the tailings dams guides suggest the mine to develop a proper surveillance program to detect possible causes of failure. Machine learning applications currently have been adapted throughout multiple engineering fields. However, the mining industry just recently started to possibly implement it into the daily operation. Parameters suggested to be monitored by the guides mostly require visual inspection, and UAV technologies are convenient and most effective for this task. Though UAVs are not foreign to most mine operations, the combination of rill detection with machine learning and UAV data is promising to aid the extensive in-person visual inspection of TSF walls. In addition, the automation will help solve the constant changes of managerial within the operation. This dissertation serves as proof of concept in utilizing semantic segmentation with UNet architecture and weighted cross entropy loss function for the detection of rills on tailings dams. The final model showed a promising result with precision, recall, and F1-score of 83.3%, 72.0%, 77.2% respectively.

Keywords: Tailings dams, machine learning, convolutional neural network, CNN, semantic segmentation, rill erosion, tailings dam monitoring.

DEDICATION

I dedicate this dissertation to my beloved dad. Your example gave me a reason to pursue graduate-level education just like you did and not quit. I wish you could be here in person so see it, but I know you are from heaven. Love and miss you dad.

Kbalue unambu bahe swok ge, swey tro me tra.

Yahe kok, tgop sni cie.

ACKNOWLEDGMENTS

This research and dissertation can only happen with the help of many parties. I wish to thank the best advisor I could ever ask for, Dr. Javad Sattarvand. Thank you for your extensive knowledge, wisdom, and patience that cannot be underestimated throughout these past two years. I would also like to acknowledge Dr. Masoud Zare Naghadehi for his relentless help and guidance throughout the research and editing process of this dissertation. Next, I would like to acknowledge Dr. Ebrahim Emami Gohari for his invaluable insights during the whole process of the machine learning portion. I would like to express my deepest appreciation to my committee members which also include Dr. Behrooz Abbasi and Dr. Poria Fajri who play a major role in the completion of this research.

This research can only be accomplished with a lot of financial help. I am extremely grateful to the National Institute for Occupational Health and Safety (NIOSH) for funding this research under the “Capacity Building in Artificially Intelligent Mining Systems (AIMS) for Safer and Healthier Automated Operations” project. I am also deeply indebted to the Papuan government through the scholarship program “Seribu Doktor” that allowed me to come to the United States of America.

Finally, I would like to extend my gratitude to all my mentors and my fellow graduate students within the Mackay School of mines. Their helpful advice, encouragement, and constructive criticism have been detrimental in expanding my point of view.

TABLE OF CONTENT

TABLE OF TABLES

TABLE OF FIGURES

LIST OF ABBREVIATIONS

TSF: Tailings dam facilities

CNN: Convolutional Neural Network

TP: True Positive

FP: False Positive

TN: True Negative

FN: False Negative

UAV: Unmanned aerial vehicle

USV: Unmanned surface vehicle

CV: Computer vision

ML: Machine learning

SME: Society for Mining, Metallurgy, and Exploration

NIOSH: National Institute for Occupational Safety and Health

DEM: Digital elevation model

RGB: Red, green, and blue

ENet: Efficient Neural Network

CHAPTER 1 : INTRODUCTION AND RESEARCH OBJECTIVE

1.1 Introduction

Recently, the topic of tailings impoundments has been trending in the mining industry. However, the big tailings dam failure in early 2019 in Burmadinho, Brazil made the industry to take an even closer look at this issue. Before further exploring this topic, it is necessary to define some general terms for a better context. The Canadian Dam Association (CDA) represents a dam as a barrier which can retain a minimum of 30,000 m^3 water, tailings, or other substance containing water (CDA, 2013). The SME Mineral Processing & Extractive Metallurgy Handbook explains that tailings are simply the remaining product after the process of mechanical and chemical extraction of ore material (Lupo & Scharnhorst, 2019). A definition from the International Commission on Large Dams (ICOLD) Bulletin 181 sums up tailings dam as “an engineered structure, comprising the confining embankment and associated works, designed to contain tailings resulting from ore processing and to manage associated water” (ICOLD, 2019). It is essential to know that this structure can be addressed with a couple of different names such as residue disposal area, tailings impoundment, tailings management facility, or tailings storage facility (TSF). This thesis will first discuss some general information about tailings dams, including how they are constructed, operated, maintained, and reclaimed. Then it will get into the central part of the research project of creating a Convolutional Neural Network model to identify rill features on dam embankments as an aid to the monitoring process.

As defined before, tailings do not hold any economic value for a site. Its combination with water results in volume expansion; thus, the disposal is tricky. The disposal method can vary depending on the site location. The ICOLD Bulletin 106 presented five ways of disposal, including economic utilization, river or sea release, underground storage, filtering and storing on land, and building a containment structure. The utilization of tailings for economic purposes is rare to find. However, it is usually related to the underground deposition, where tailings are mixed with cement to serve as backfill material. This is especially useful for operations with weak rocks. Subaqueous disposal is another name used for river or sea disposal, which is exactly as the name implies. Tailings are deposited under a body of water after being treated. An example of this application is the Indonesian operation of the Freeport-McMoRan. The site is in the highlands of Papua, where high precipitation in the area will create severe difficulty in the case of a regular surface dam, so the operation is releasing it to a river that travels down to the ocean. Tailings containment in a dam structure is what commonly used in the industry to retain tailings material on surface with multiple variations of how to retain it. Another name used for this method is subaerial. The containment facility usually requires a large area to fit all tailings produced, so tailings are typically transported and deposited some distance away from the processing plant. Steven Vick (1983) explains that the optimal distance between the tailings dam and mill facility is within 5 miles away. Dry tailings disposal on land is another option where no impoundment structure needed. Water was filtered out for reuse, and the remaining material can be placed and compacted somewhere else. The subaerial method is where most accidents arose, so the focus from this point forward is on this disposal method.

Proper containment of tailings is a vital aspect of making sure that the material will not flow out and disturb the surrounding area. Therefore, this correlates to the health and safety of the employees, the environment, and the operation itself. Two typical tailings discharge types for surface impoundment are using spigot or with single-point discharge (Figure 1). Many operations employ spigots to control material distribution and reduce workload because single-point discharge is less flexible (Fell et al., 1992).

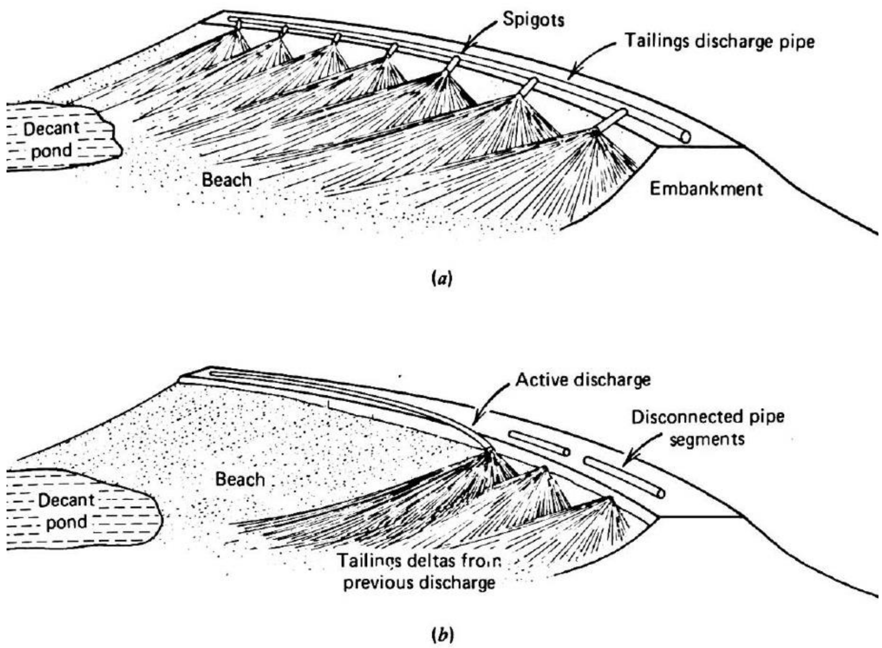


Figure 1: Tailings material discharge methods. (a) Multiple spigots. (b) Single-point discharge. (Vick, 1983)

Decant pond will always be present inside the TSF except for filtered tailings. There are two conventional methods to control the amount of decant pond, such as with floating barge and having a built-in decant tower (see Figure 2). The use of a floating barge on the surface of impoundment is preferable because of its mobility. On the other hand, the tower will only stand in one place, which requires careful placement planning and operation to direct the water. Before discussing different layouts of dam configuration, we need to acknowledge that each tailing is very different from one another. This difference can be attributed to the different ore characteristics, the various processing steps, and the water amount retained. ICOLD Bulletin 181 listed some types of processing that can be done to the material (2019):

- Mineral recovery through crushing, grinding, and chemical.
- Ore upgrade through the beneficiation of unwanted materials removals.
- Washing of coal, sand, and clay.
- Residue collections from coal combustion, blast furnaces, etc. to take ash and slag.
- Chemical reactions within a process that create by-products (e.g., gypsum).

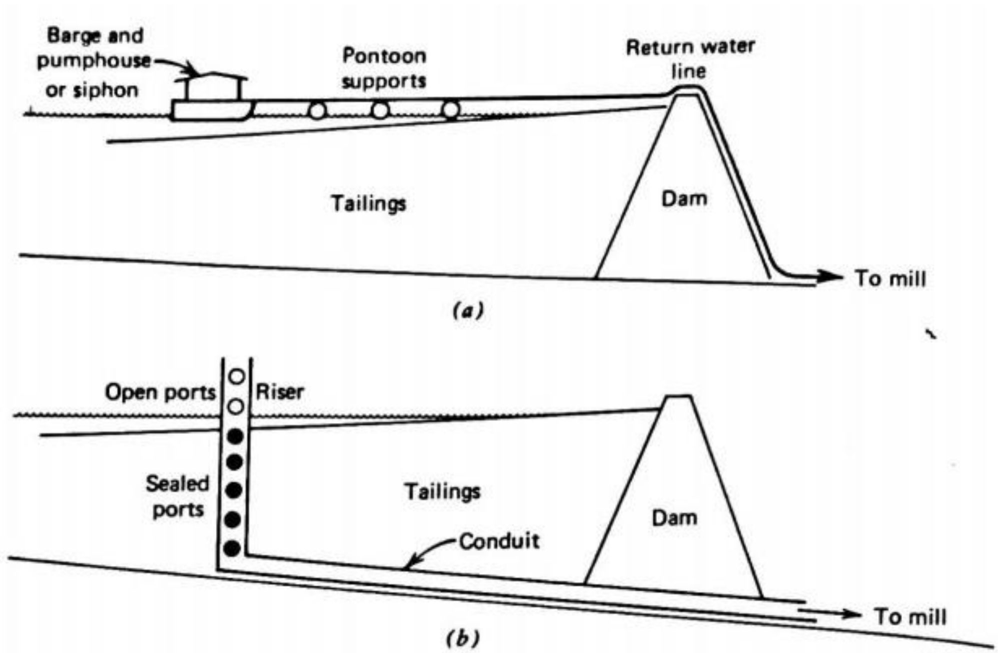


Figure 2: Decant methods to control pond quantity. (a) Floating barge. (b) Decant tower. (Vick, 1983)

Tailings can be classified based on the degree of material gradation and plasticity. Vick (1983) discussed and grouped tailings into four classes, including soft-rock, hard-rock, fine, and coarse. Also, Bulletin 181 (ICOLD, 2019) expanded this classification into five categories: coarse tailings, hard rock tailings, altered rock tailings, fine tailings, and ultra-fine tailings. The followings are the definitions of each class (ICOLD, 2019 and Vick, 1983):

- Coarse tailings: Cohesionless soil with medium to high shear strengths. Physically describable by silty sand and non-plastic material.
- Hard rock tailings: Sandy silt with non to low plasticity. The material shows angularity and good shear strength. Tailings material of most known minerals (Gold-silver, copper, etc.) is in this category.
- Altered rock tailings: Special for rock that has gone alterations with shear strength depending on the quantity and type of clay fraction. It has a low plasticity.
- Fine tailings: Material has low to moderate plasticity with small or no sand fraction generally. An extended period of sedimentation and consolidation may be required, thus needing large volume and impoundment areas.
- Ultra-fine tailings: It has high plasticity but low hydraulic conductivity and density. Fast drainage is required to aid the consolidation process.

The SME Mineral Processing & Extractive Metallurgy Handbook recorded another way of tailings classification based on the moisture content. This classification will determine how to design and manage the tailings material. Figure 3 shows how water content affects the transportation method, operation costs, and capital costs. Trade-off study during the site evaluation process could be less stressful by looking at this classification based on the water content (Lupo & Scharnhorst, 2019). The classification type relates to which ore processing method being utilized.

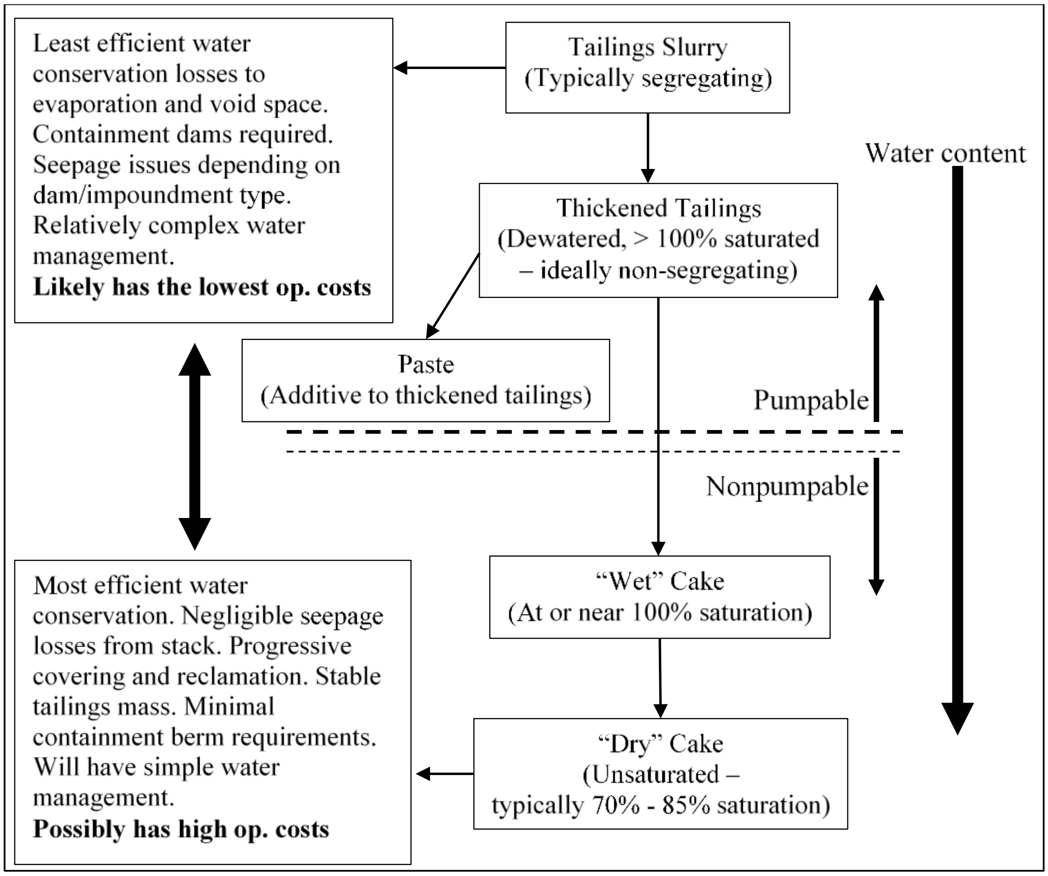


Figure 3: Tailings classification based on their continuum. (*Adapted from* Davies & Rice, 2001)

Subaerial or surface tailings disposal can be classified into two main classes: water-retention type dams or raised embankments (Vick, 1983). Vick (1983) suggested the use of water-retention type when the site requires high water storage for the walls are equipped with a core filter in the middle to control the seepage and avoid failure. On the other hand, there are multiple options of raised embankment configuration that can best fit the terrain of the proposed location. Figure 4 presents the layouts available to choose from, and it does include a variation where tailings are transported into an abandoned pit. Mentioned configurations are applicable for any type of tailings classification from gradation percentage and water quantity perspectives.

Below are brief explanations of each layout (Kerr & Ulrich, 2011; Vick, 1983):

1. **Cross-valley**: The traditional water retention dam commonly uses construction. The setting is in between a natural valley or drainage path of the basin, where natural topography is utilized. Only one wall is required for containment. It can be expanded to have multiple levels going down the valley, if possible.
2. **Sidehill**: This layout requires more walls constructed compared to cross-valley. Three walls are enclosing the impoundment on the side of a hill. However, hill slope should be less than 10% and available for various constructions.
3. **Above-grade**: Other names of this layout are paddock and ring dikes. It requires the construction of all four walls around the dam, and it is suitable for flat areas such as Nevada. The final configuration can be in one large impoundment or segmented into multiple small sections.
4. **Below-grade impoundment**: This layout is mostly known as in-pit disposal where tailings are stored within an inactive pit. It is very convenient since no wall construction needed but can only be used after mining activity is completely done in that pit.
5. **Above-grade stack**: This is the particular case for filtered tailings. The lack of water content allows tailings to be compacted without enclosing it with walls.
6. **Combination with waste rock**: Comingling is another name used for this method. Tailings with medium to high water content are stored together with waste rock

dump. Tailings are supposed to fill the space between the rocks, thus saving capital investment for building a new impoundment.

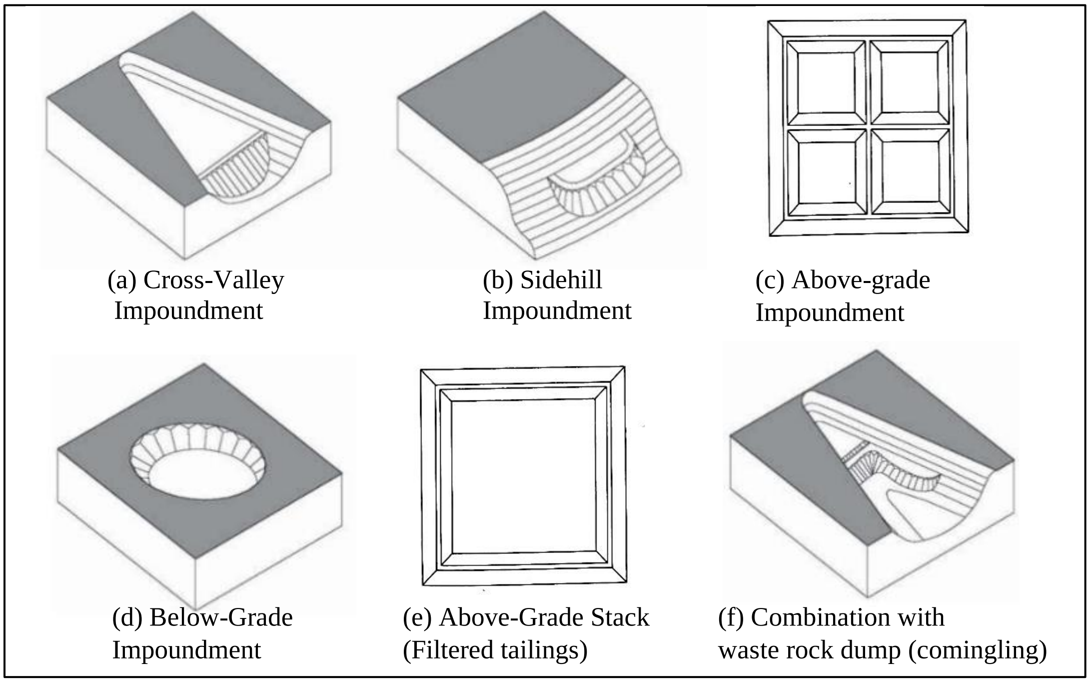


Figure 4: Tailings dam layout depending on the terrain of future dam location. (Kerr & Ulrich, 2011; Vick, 1983)

Determination of raising method is the next step after choosing the layout suitable based on the location of a mine site. There are three raising methods currently in use: upstream, downstream, and centerline (see Figure 5). Most TSFs are using upstream raises due to their low operating and capital costs; however, this method does not usually have a good stability condition in active seismic areas (Kossoff et al., 2014). The naming convention is based on which direction the embankment crest moves from the starting dam. A short description and summary of each method are presented as follows (ICOLD, 1996a; Lupo & Scharnhorst, 2019):

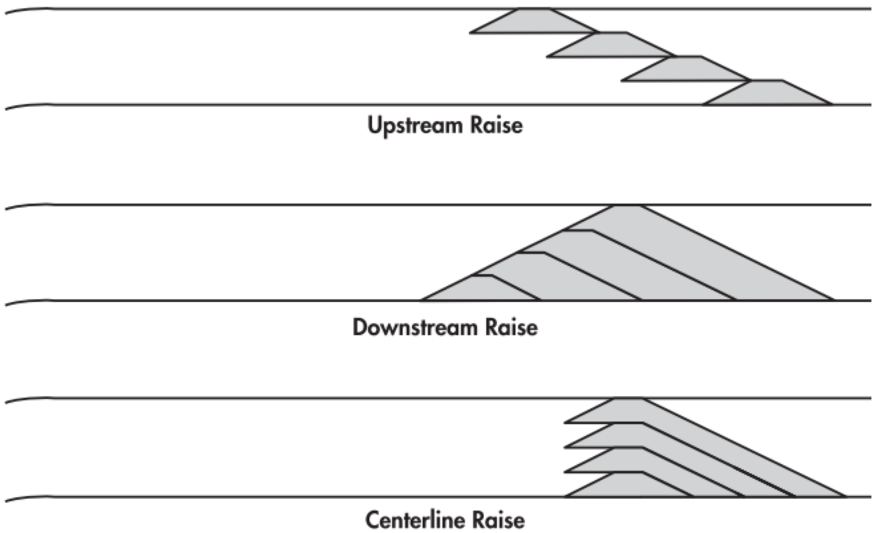


Figure 5: Embankment types based on the raising method. (Lupo, J; Scharnhorst, 2019*)*

1. **Upstream**: This is the most common method where the second and later dikes are located upstream from the starting dike. The raised dikes are placed on top of the tailings material. This does not require a lot of material to build the dikes; this is most favorable due to its simplicity and low cost. However, it should only be used in dry climates and inactive seismic areas. An essential aspect of the upstream method, aside from the low construction cost, is a proper drainage system.
2. **Downstream**: This method is the least used one in the list. The second and later dikes are located downstream from the starting dike. Unlike upstream, the dikes are placed on top of the prior dike. This method makes a very stable dam, hence reasonable to reduce the risk of slope failure, especially in seismically active areas. Chile requires all TSFs in the country to use this method for better stability reasons. However, it is considered expensive since a large volume of material is needed to be moved.
3. **Centerline**: This is a method combining upstream and downstream techniques. The fill volume is not too little nor too big. The location of the second and later dikes

are precisely on top of the previous dike. The centerline method is gaining more popularity, so some sites would modify it to fit their needs to slightly lean to the upstream or downstream direction. However, the extent of filling material placed on top of tailings should be appropriately planned since it also relies on the strength of tailings materials for stability.

The selection process of the construction method will need considerations on water management, engineering process, geotechnical, environmental, and social aspects (Lupo & Scharnhorst, 2019).

One more critical concern in embankment construction is the material selection for the wall/slope. The Australian National Committee on Large Dams (ANCOLD) suggested testing various materials for this purpose. The type of tailings contained will influence the strength required by the embankment. This is especially crucial for the downstream method. Also, the selected material will take part in controlling the phreatic surface (Vick, 1983). This selection should be made from the beginning to check if enough material is available in the site or, in the worst-case scenario, need to be transported from elsewhere.

A couple of options for dike material are natural soils, mine waste, and cyclone tailings (Vick, 1983). Natural soils are the materials available on the site that meet the design criteria. This option will not only reduce the operation and capital cost but also increases the capacity if excavated within the storage basin. However, this method should be utilized only if the soil can support the whole construction period. The second-best alternative is using waste rocks. It is also an option with a cost advantage since material haulage will be combined with the waste rock haulage. ANCOLD (2019) recorded that weathered mine waste usually serves this purpose best, but the rocks should be tested in advance if it has the potential to result in an acid drainage problem in the future. An additional issue might be the difficulty of controlling the material size distribution. Waste rocks were extracted by blasting the material, so it might have less focus on the resulting rock size. The last option is the utilization of tailings material itself. This method employs hydrocyclone to separate the slimes (overflow) and coarse sands (underflow). The underflow will become the material used to raise the embankment while the slimes are contained inside. It is advantageous when there is not enough available suitable natural soil, but the material compaction method would be something that needs to be thought of when selecting this option (Vick, 1983).

There are other considerations required to properly design a TSF such as hydrogeologic studies, water management, environmental, liners, and tailings rheology, to name a few. All of these are vital since it will lead to site reclamation at the end of the project (ICOLD, 1996a). The items explained in this sub-section are the ones directly related to the dam walls, which is the main topic of this study.

1.2 Background

Tailings impoundment is mostly considered as liability for a mining operation. It does not produce any valuable product, but it requires constant maintenance and monitoring throughout its life cycle (this includes even post-closure efforts). All of these are crucial for failure detection and prevention. Most people might associate dam failures with catastrophic events that cost the lives of people and environmental damages. These significant accidents are usually related to a type of stability failure.

Failure is always a concern with TSFs. The failure rate of the tailings dams worldwide is estimated at 1.2% compared to the 0.01% rate for traditional water dams based on data from 100 years (Lyu et al., 2019). Rico et al. (2008) found that an active tailing dam contributed over 85% of failure occurred in the world at that time. The current high metal demand is projected to require more mining, thus continual waste creation, which leads to even more active tailings dam. Damage is prone to happen in on tailings dam walls compared to water retention dam wall for the following reasons (Lyu et al., 2019):

1. The use of residual material for dike construction.
2. A linear relationship between the dam height and the amount of wastewater.
3. Minimum regulations are provided in the dam design standards; and
4. High monitoring cost when active and after reclamation.

The main goal of this research is to aid the tailings facility using drone technologies and machine learning application, so point four of the reasons listed above would be the main concern of this study. The author hopes that this research can lead to creating a method that lowers the high monitoring cost.

ICOLD Bulletin 121 summarizes the causes of reported tailings dam failures around the world, which sparked the interest to create a database of failures posted on a website entitled www.worldminetailingsfailures.org. An additional source where TSF failures are frequently recorded is a website by the World Information Service on Energy (WISE, www.wise-uranium.org). It focuses on Uranium mines, but it provides a compilation of major tailings dam failures from 1960 to present and gives details of the incident type, the amount of material released, and the impact of failure. After compiling reviews from TSF guidelines, papers, and databases, many failures were caused by seepage, foundation failure, overtopping, and earthquake. This list is also reflected in the data shown in Figure 6. Out of those causes, this study is directed toward overtopping to see how well we can detect its leading features for better tailings dam monitoring using image analysis.

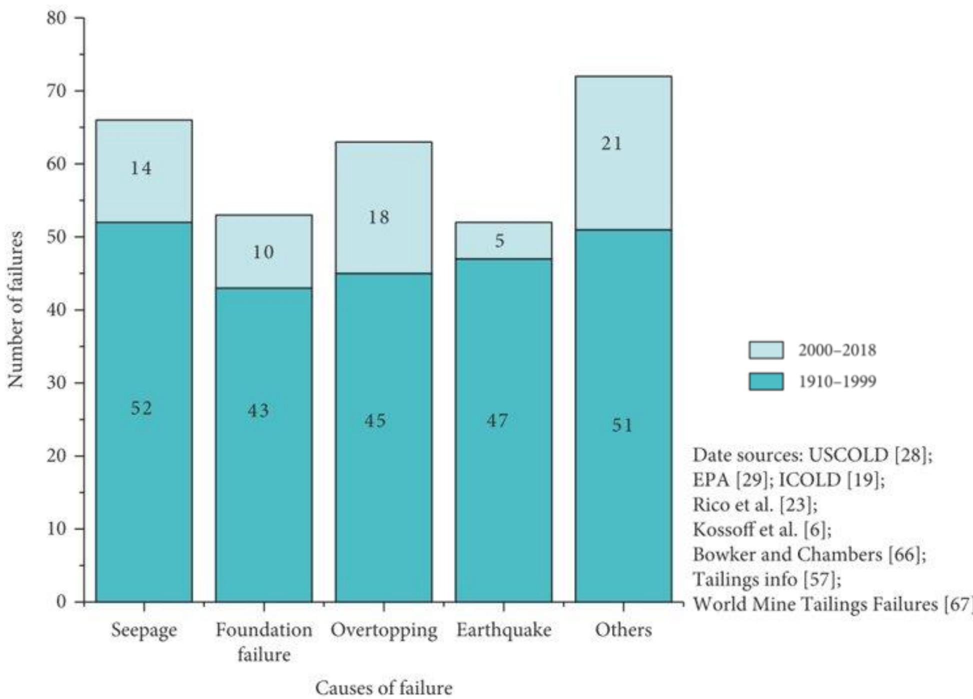


Figure 6: Main causes of failure in TSF based on 100 years data. (Lyu et al., 2019)

The identification of these failure causes can be made through several performance parameters. Table 1 presents a compilation of some essential categories summarized by Clarkson and Williams (2019). This list indicates that there are ways of preventing these failures. A study recorded in a review paper by Lyu et al. (2019) found that the initial stages of overtopping can be mistaken as signs of water erosion. The Federal Emergency Management Agency (FEMA) recognizes that a small failure can lead to a more significant event (2004). Erosion itself is shown in Table 1 as one of performance parameters to be monitored on the embankment. Out of the four types of erosion listed, rill erosion is the most logical to be monitored constantly

Table 1: Compilation of key visual performance parameters. Adapted from Clarkson & Williams, 2019

Category	Visual Parameter
Tailings Surface	Reservoir level and freeboard requirements Size and position of the decant ponds Slurry flow rate and density Tailings delivery system: deposition position, condition of piper and valves Beach slopes A persistent vortex (whirlpool) in the reservoir that is unrelated to operational outlet works
Ancillary Infrastructure	Roadways and access condition/erosion Decant facility integrity and access Return water storage capacity and infrastructure Condition of gates, fencing, and signage Pump and pipeline systems condition Cracking in any concrete structure Vegetation clogging drainage ditches Discharge tunnel or conduit condition, seeps, and cracks
Emergency Preparedness	Status of the leak detection system, secondary containment systems, automatic flow measurement, and fault alarms
Seepage Flow	The efficiency of trench flow Density and flow rate of slurry New development or changes in seepage areas The color of seepage water (meaning carrying sediments) Quantity, location, and clarity of flowing water
Instrumentation	Water levels Condition of monitoring instruments and data reading quality
Embankment/Berms	Cracking toward any direction or plane Toe bulging Subsidence at the crest or any part of the downstream embankment Sinkholes at the bottom of the reservoir or the upstream face of the dam New vegetation or changes in quantity Surface erosion – splash, sheet, rill, or gully Weeping Piping

	Sloughing Wave erosion on the upstream embankment
Miscellaneous	Wildlife

Finally, the goal is to prevent failure from occurring. Once an impoundment fails, it damages the environment and takes human lives (Lyu et al., 2019). Amstrong et al. (2019) recommended some technical and managerial level incentives that might prevent failure, such as the use of new processing technology, impose significant penalties, and adopt the MAC guideline. He believes that the MAC guideline's inclusion of higher-level officials will push more care to the tailings facilities. It is common in the mining industry to go through changes of management and TSF personnel, so another challenge is to make sure that proper maintenance and high safety standard are being carried out throughout the life of facility. The current advancement in technology had incentivized mining and consulting companies to employ UAV and USV technologies. They have been proven to effectively conjunct the traditional monitoring process while active (Jeong & Kim, 2019) and post-reclamation (Slingerland et al., 2018). Therefore, the automation of monitoring system coupled with new technologies (i.e., drones) would assist with continual monitoring in the case of managerial changes.

1.3 Objective and Scope of Research

The objective of this study is to detect and analyze signs of rill erosion on the tailings dam slopes. Water is always present in tailings dams, especially if the decant pond is present and/or the TSF is located in a high precipitation area. In the topic of structure stability, the majority of guidelines recommend proper strength maintenance of the dam structure throughout and beyond the life of TSF. However, the process of erosion will naturally take away the material on the dam slope, causing mass loss, thus resulting in the loss of dam strength. Rills can then develop to gullies as more water quantity flow through, thus detecting it could also serve as a new possible overtopping location. Therefore, this study could add to creating a better monitoring program identifying the initial stages of the top two failures shown in Figure 6 i.e., overtopping and slope instability.

The main scope of this research is rill erosion analysis through image processing and Unmanned Aerial Vehicle (UAV) data. The use of UAV will address the issue of accessibility of typical mine facilities, large-scale coverage, and a variable height of data acquisition (Battulwar et al., 2020). Visual inspection is still a significant part of the monitoring process; therefore, image analysis can provide an efficient inspection of the dam slopes on a large scale. It can simply help isolate certain places that might require extra attention for an in-person inspection.

1.4 Methodology

The approach of this study starts by going through different guidelines on tailings dam design, monitoring, and management, then isolating the parameters where visual inspection is required. It is then followed by determining which parameter would closely link to one of the significant causes of failure. After further analysis and literature review, water erosion (shown as rills) can serve as an indicator of overtopping and loss of material transported by the water contributing to slope instability.

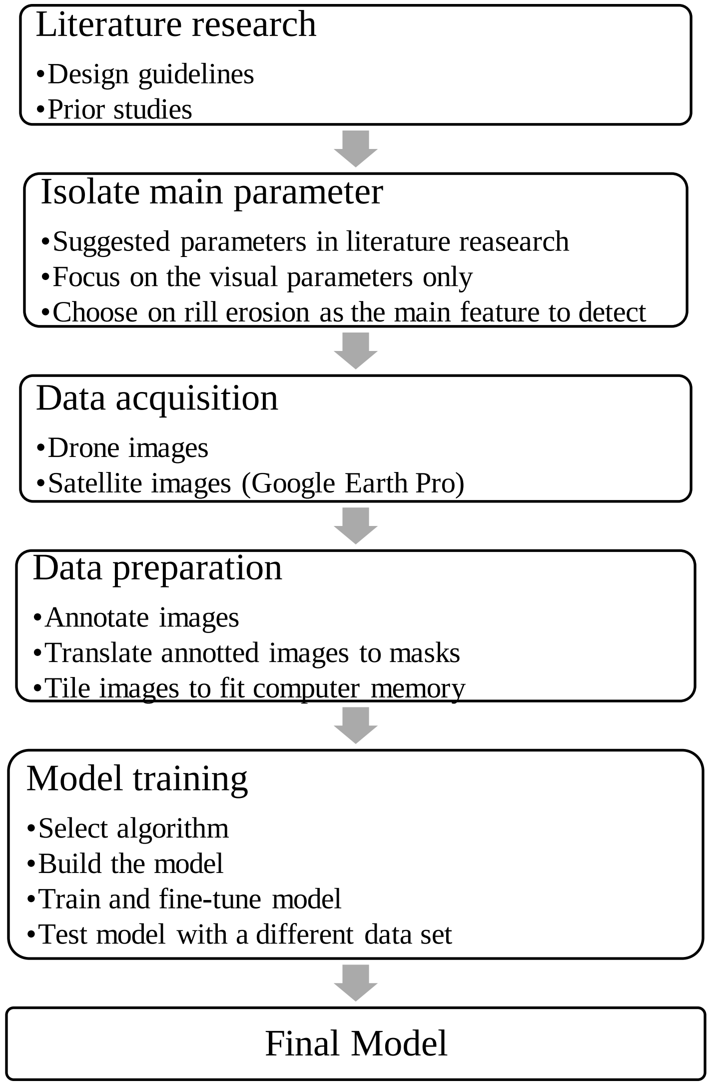


Figure 7: Flowchart of research steps of the thesis

When working with a machine learning application, the initial image database plays an essential role. The drone data is gathered from flying sessions in the local area, from multiple partnered mines, and satellite images from the Google Earth Pro application. The images are then prepared with an image editor software combined with Matlab to create labeled images and masks for model training. The foremost step is the training of the machine learning model. Convolutional Neural Network is selected as the main algorithm where the project is formed as a semantic segmentation problem. The model is trained to detect two classes, namely 'rill' and 'background (not rill).' This training process takes place both in Matlab and Python environments, and the latter comes out as the most convenient environment to debug and adjust sections of the codes when needed. The model fine-tuning and testing steps are also performed using a Python code for the sake of simplicity and continuity. Figure 7 shows a simplified flowchart of this thesis research.

1.5 Thesis Structure

This thesis is divided into five chapters. Chapter 1 focuses on introducing the research topic, background information related to failures in tailings impoundment, laying the reason behind this topic, giving the extent of this research, and closed with a general flowchart of the study in the methodology section. Chapter 2 is allocated to reviewing the dam design guidelines from around the world, focusing on isolating the parameters suggested to be monitored visually. After the compilation of these parameters, each of them is given a brief explanation of what it is, why it is monitored (related to possibly leading to failure), what caused the development and advancement of this parameter, and if there are any studies associated with enhancing the monitoring process. A review of the current TSF monitoring system is provided in this chapter as well. This chapter is then closed by a discussion about the application of remote sensing and machine learning in the mining industry. Due to the nature of this study, Chapter 3 is dedicated to a brief explanation of Convolutional Neural Networks (CNN), which is the employed algorithm in building the machine learning model. Chapter 4 discusses explicitly the primary analyses and results of this research, which includes building a machine learning model that can detect rill erosion features on images. This contains how the data are acquired and prepared, as well as the training process and the resulted model. The very last chapter, Chapter 5, wraps this thesis by summarizing the work and presenting a conclusion along with recommendations to create a better model, and possible further research on this topic.

CHAPTER 2 : LITERATURE REVIEW

2.1 Introduction

Based on a database by the National Inventory of Dams, there are a total of 91,468 dams in the whole US, which includes the minoring islands of Puerto Rico, and Guam. Out of that, only 1,233 dams are tailings dam (see Figure 8), which is only 1.4% of the total number. However, case history proves that the rate of failure in the tailings dam is higher. The statistic shows that the average of three tailings dams fails annually (Lyu et al., 2019).

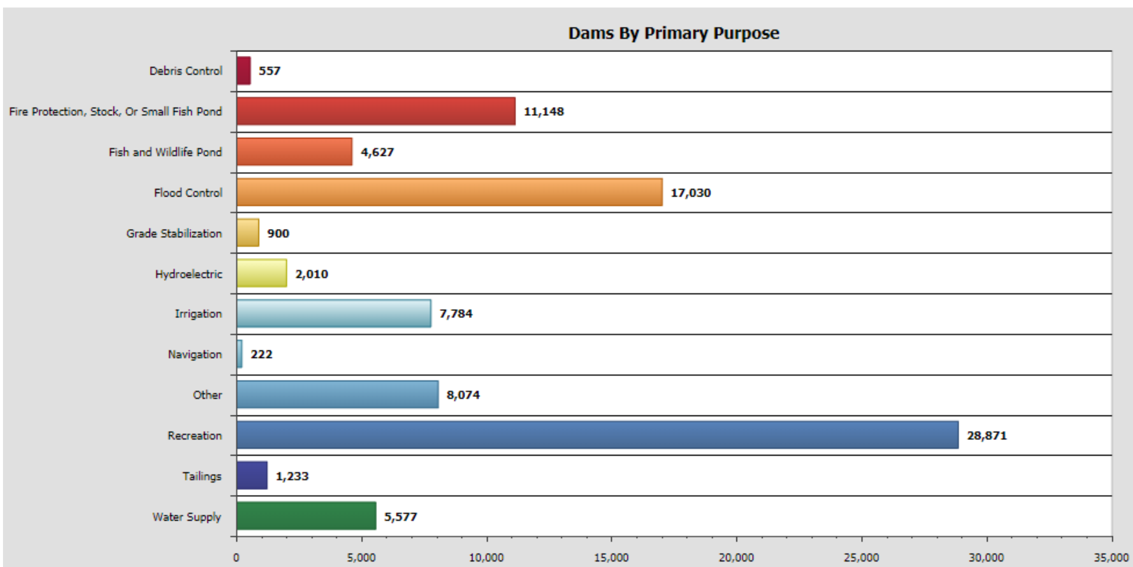


Figure 8: Dams classification based on the purpose of dams across US lands. (USACE, 2019)

This high failure rate had incentivized many organizations and countries to provide better tailings dam design guidelines to follow. Currently, three countries have been very active in enforcing these guidelines, such as Australia, Canada, and South Africa, which have very high mining activity and tailings dam inventory (Dixon-Hardy & Engels, 2007). The next section will dive into some guidelines that are commonly used during the design, operation, and maintenance of TSF. Tailings dam is very site-specific, so countries publishing guides will include common practices there. Also, some of these guides can be utilized for both tailings and general dams in the construction process.

2.2 Guidelines for tailings dam design, operation, and maintenance

There are multiple guidelines currently available in tailings dam construction. Dixon-Hardy and Engels (2007) summarized those guidelines based on the country of origin and some independent organizations, such as Canada, Australia, South Africa, International Commission on Large Dams (ICOLD) and its member countries, United Nations Environmental Program (UNEP), and the International Council on Metals and the Environment (ICME), the International Institute for Environment and Development (IIED), and the International Organization for Standard (ISO). However, IIED only deals with safe disposal into the natural body of water, and ISO serves as an extra layer of certification since ISO 14001 was the guide in constructing one of Canada's famous guidelines, the Mining Association of Canada (MAC). This section of the literature review will give a general review of the guidelines and their contribution to the monitoring system of tailings dams.

The Church of England in April 2019 requested a disclaimer from all mining companies on their list of tailings dam active and inactive in response to the Brumadinho dam disaster in Brazil back on January 25th, 2019. Table 2 shows the result of this survey, where only 85 companies are willing to disclose the full list of their tailings impoundment. Out of the 85 companies that responded, 31 of them employ the Canadian Dam Association (CDA) as their basis to create their site-specific operational manual. The Australian

National Commission on Large Dams (ANCOLD) is also popular with a total use by 25 companies.

Table 2: Survey result conducted by the Church of England

Classification	Amount
Total	726
Overall Responder	290
Declared no TSF	164
Full TSF Disclosures	85
All Disclosures (partial included)	126
No Response	436

Table 3 presents the frequency of applied guidelines used by those companies. Note that some companies own sites on multiple countries, especially in South Africa, where all TSF need to follow the SANS regulations, so they utilized various guides. The total itself is not 85 precisely because there are companies located in Russia and in the former Soviet Union countries that are using their own country's laws and regulations.

Table 3: Popularity of tailings dam guidelines among the survey responders

Guideline/Standard	Number of uses
CDA	31
MAC	5
ANCOLD	25
ICOLD	1
ISO	1
SANS	14

The following subsections will consist of a small explanation of the guidelines listed in Table 3 and some additional standards that are periodically used in the mining industry. Due to the nature of this study, the documents discussed are the ones specified for tailings dam monitoring. The trend among these guidelines revolves around *Why should we monitor it? How to monitor it? What are the effective instruments or methods to use?* Most monitoring systems need to be installed since the beginning; therefore, good planning will result in an efficient data gathering.

2.2.1 Mining Association of Canada (MAC)

As given in the name of the organization, this guideline was produced in Canada using the Canadian standard. The organization consists of 41 companies that are considered as full members and 57 associated companies. MAC is an organization that focuses only on sustainable mining in Canada and help support their members and partners. There are two main guides published and revised throughout the years, including *"A Guide to the Management of Tailings Facilities" –The Tailings Guide,* and *"Developing an Operation, Maintenance, and Surveillance Manual for Tailings and Water Management Facilities" – The OMS Guide*. The tailings guide has three editions published where the latest edition was updated in 2019 (Version 3.1).

On the other hand, the OMS guide has two editions, and the second edition was revised in 2019 as well. All guide documents are available online for download at MAC's main website. This thesis deals with monitoring on the tailings dam, so this section will focus on the OMS guide.

The OMS guide gives great information and expansion of the reasoning of creating a surveillance system. The term surveillance in MAC covers both inspection and monitoring. The idea behind monitoring is to see a possible trend within the recorded data and inspect the performance of the facility. Each site should keep in mind how its surveillance program is designed that can best fit their needs (MAC, 2019b). There are two types of surveillance activities suggested in MAC such as site observation and inspections and instrument monitoring.

The use of UAV is a part of the first activity i.e., site observation and inspections where visual changes are inspected and monitored. Examples of potential observations given are related to physical risks, chemical risks, tailings material and water transport, flora and fauna, and surveillance instrumentation on the ground. In summary, the parameters suggested are:

- Pond level and freeboard
- Deformation (bulges, cracks, sinkholes, etc.)
- A new or expanding area of erosion
- Piping or unexpected water movement
- New seeps formation, changes in seeps, or changes in seepage characteristics
- Spigot or material discharge instrument and pump condition
- Possible leakage of water lines from the decant pump
- Condition of water reclamation infrastructure
- New or change in wildlife activity
- New or changes in vegetation
- Condition of the ground instruments

MAC is showing a detailed aspect of tailings dam management where it requires extra precautions that covers every part of TSF.

Furthermore, the tailings dam guide does include a small section dedicated to TSF surveillance. It ties the responses and preparedness of emergency when the surveillance system picks up anomalies or risk of failure. However, the implementation of this management guideline should be paired with the OMS guide (MAC, 2019a).

2.2.2 Canadian Dam Association (CDA)

The Canadian dam association is another guideline that originated from Canada and the most popular out of the guides given in Table 3. Both CDA guidelines and technical bulletin recognize routine inspection as an important aspect of a good dam safety management system. Figure 9 presents this as the first step of the dam safety analysis process but notice that the system should run as a closed-loop.

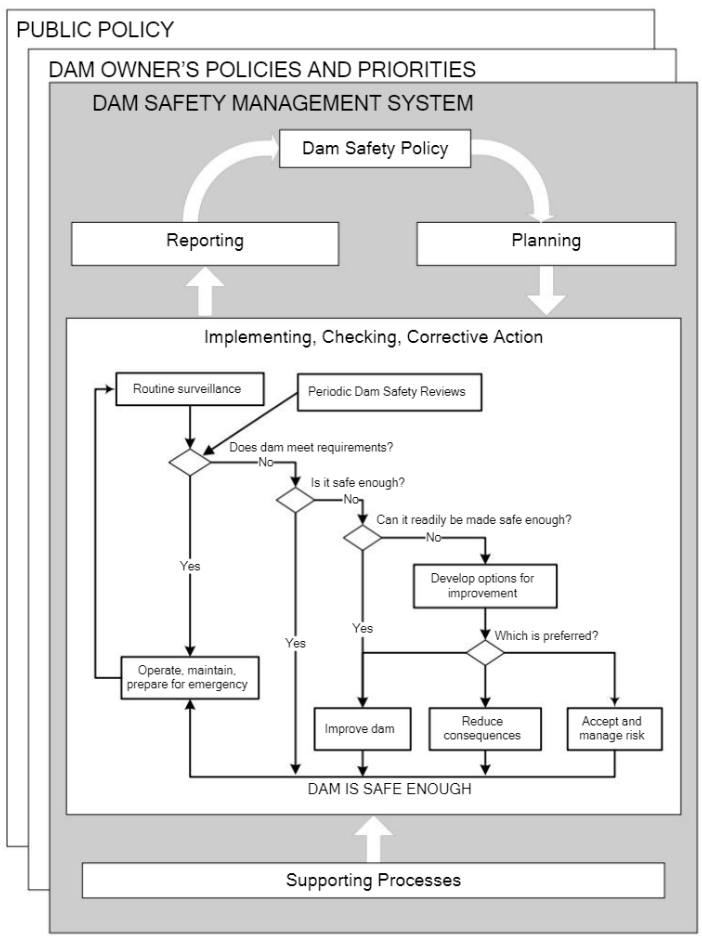


Figure 9: The suggested dam safety management system for the tailings dam. (CDA, 2013)

This guideline recommended that dam surveillance can only be effective when the site understands the possible failure modes, signs of failure to look for, and the proper monitoring or inspection measures to detect such process. Principle 4a of the guideline said that *"A safety review of the dam shall be carried out periodically."* It advised an evaluation and systematic review of all aspects including visual inspection of various dam components since warning signs usually appear as dam failures develop (CDA, 2013). To simply put it, the parameters that we should visually monitor in routine are:

- Leakage
- Erosion
- Sinkholes
- Boils
- Seepage
- Slope slumping or sliding
- Settlement
- Displacements or cracking of structural component
- Clogging of drains and relief wells, etc.

The frequency of inspection is greatly dependent on the regulatory requirement, the consequence of failure, season, development time, etc.

2.2.3 International Commission on Large Dams (ICOLD)

ICOLD is an organization that targets countries around the world where they can become the member or extension within their own countries. Currently, there are more than 100 member countries from all continents. Each country member can publish their guideline created specifically for their specific law and geological condition. The United States is a country member and known as the United States Society on Dams (USSD). Tailings dam is categorized as an industrial waste dam in USSD. There is no published guideline specific for TSF by the US branch, but they are very active in creating workshops to share knowledge and information. The general publications on dams from ICOLD were released in bulletins where each bulletin talk about different topics related to the different kinds of dams. To name a few, it covers challenges in dam engineering, concrete dams design, surveillance, safety management, water storage, regulations, material selections, inspection guidelines, risks, lessons learned from past cases, etc. The following are the published bulletin specified for tailings dam from the latest release:

1. Bulletin 181: Tailings dam design – Technology Update (2019)
2. Bulletin 139: Improving tailings dam safety – Critical aspects of management, design, operation, and closure (2011)
3. Bulletin 121: Tailings dam risk of dangerous occurrences – Lesson learnt from practical experiences (2001)
4. Bulletin 106: A guide to tailings dam and impoundments – Design, construction, use, and rehabilitation (1996)
5. Bulletin 104: Monitoring of tailings dams – Review and recommendations (1996)
6. Bulletin 103: Tailings dams and environment – Review and recommendations (1996)
7. Bulletin 101: Tailings dams transport, placement, decantation – Review and recommendations (1995)
8. Bulletin 98: Tailings dams and seismicity – Review and recommendations (1995)

9. Bulletin 97: Tailings dams – Design of drainage (1994)
10. Bulletin 74: Tailings dam safety – Guidelines (1989)
11. Bulletin 45: Manual on tailings dams and dumps (1982)
12. Bulletin 44: Bibliography – Mine and industrial tailings dams and dumps (1989)

Out of the 12 bulletins, four of them cover the area of monitoring/surveillance (bulletins 74, 103, 104, and 139). Seven bulletins specifically for dam surveillance are also available for review:

1. Bulletin 60: Dam Monitoring, General Considerations (1988)
2. Bulletin 68: Monitoring of Dams and Their Foundations, State of Art (1989)
3. Bulletin 87: Improving of Existing Dam Monitoring (1992)
4. Bulletin 118: Automated Dam Monitoring Systems – Guidelines and Case Histories (2000)
5. Bulletin 138: General Approach to Dam Surveillance (2009)
6. Bulletin 158 (Dam Surveillance Guide (2013)
7. Bulletin 180: Dam Surveillance, Lesson Learnt from Case History (2017)

Most of the specified bulletins are not listing the exact parameters to be monitored visually. However, this might be due to the lengthy explanation given within the general dam surveillance documents. Bulletin 180 is currently in a preprint format, but it summarizes both bulletins 118 and 158 on the idea of surveillance. Figure 10 shows a chart representing areas of surveillance and tying it to the dam assessment process. The author wants to make a note that this document indicates how visual inspection only has an analysis section since no instrument used but human eyes. This thesis is presenting a way of implementing a camera as the instrument which will feed into a machine learning model, thus representing acquisition and processing.

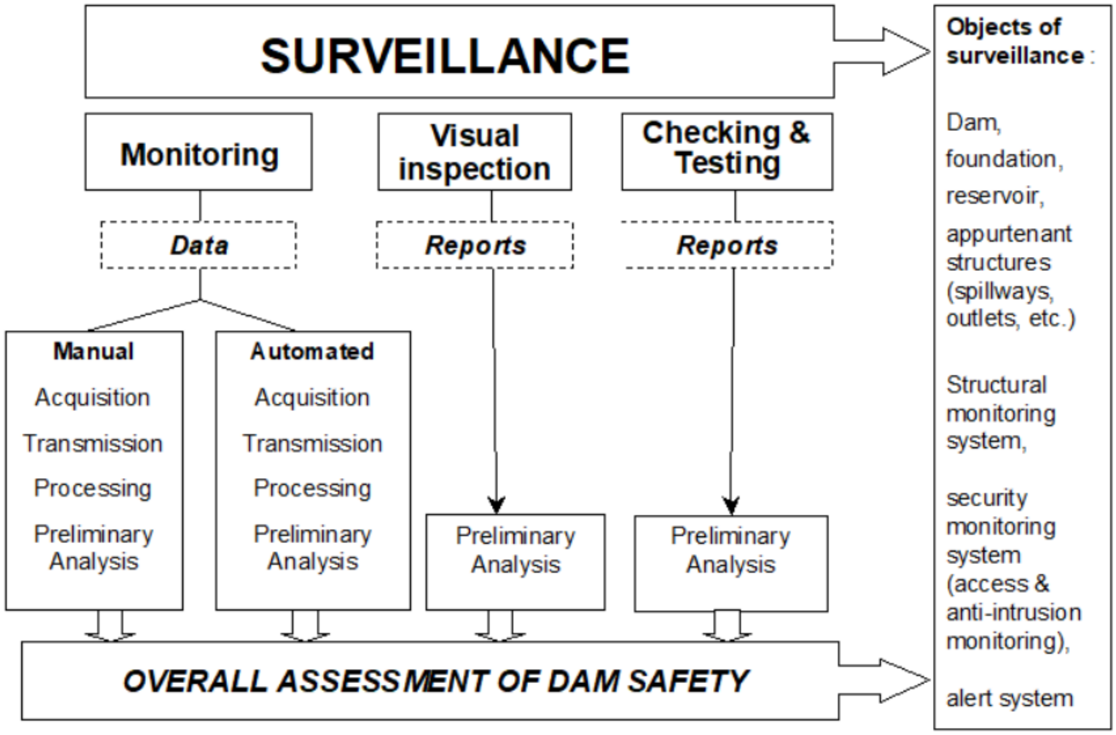


Figure 10: Graphical representation of surveillance on the tailings dam. (ICOLD, 2019).

Detailed surveillance guidelines can be found in bulletin 158 as the most recent publication on the topic. Four big items suggested for visual inspection are the following:

- Seepage
- Displacements and deformations
- Cracking
- Erosion, weathering, and clogging

Table 4 below is the adaptation of visual inspection for the embankment dam type showing the location and what to inspect. Changes summarized in this table are the ones detectable with the UAV system. The document then mentioned the case of special inspections. For

UAV applications, it is more suitable for inspection without direct access. Inspection frequency is recommended to be weekly but daily might be necessary after a major or extreme event (ICOLD, 2018). The great addition of this bulletin is how it provides recent development and application of new technology in monitoring. There is also a separate section especially on creating automation of the monitoring system.

Table 4: The extent of visual inspections for an embankment dam type. Adapted from ICOLD bulletin 158 (ICOLD, 2018).

Part of the Dam	Changes Inspected
Downstream face	Seepage water surfacing Cracks, local settlements Erosion (development of gulling) Vegetation Animal burrows
Dam crest	Cracks, local settlements Erosion Vegetation Animal burrows Road condition
Upstream face (accessible section only)	Vortex formation on the water surface Cracks, local deformations, local slides Bulging of surface sealing elements Damages in the surface sealing element Displacement or riprap Vegetation Animal burrows

2.2.4 Australian National Committee on Large Dams (ANCOLD)

As the name refers, this guideline was developed by the ICOLD country member of Australia. Like ICOLD, this organization deals with concrete dams, earth embankment, and also tailings dam. Practices for tailings initially published in May 2012 were considered as the standard in Australia, and it was used heavily in Australia and around the world. It was then revised in July 2019 to include new practices learned from failures during that time range. The most significant addition in this new publication is related to earthquakes where they learned that it could induce failure due to static liquefaction. Sites outside of Australia are advised to use this guideline alongside the original ICOLD guidelines to create a specified document that follows the local natural condition.

ANCOLD suggested a couple of types of inspections levels such as comprehensive, intermediate, routine, special, and emergency. The drone application could fall into the routine inspection which frequency depends on the failure consequence category. Furthermore, the following is the list of visual inspections recommended:

- Overtopping
- Burrowing
- Flora attack (root penetration)
- Flora colonies
- Erosion
- Cracks
- Sinkholes
- Subsidence
- Piping
- Seepage
- Movement
- Misalignment
- Deformation

- Settlement
- Freeboard levels
- Beach width
- Pond location
- Storage capacities

The guideline itself is not as detailed as an ICOLD bulletin; however, it is concise enough to serve well as a foundation to create a site-specific guide.

2.2.5 South Africa National Standard (SANS 10286)

The requirements listed in this guideline are special for the tailings dam located in South Africa where this document was published. The South African Bureau of Standard published this guideline back in 1998 in response to a failure at the Merriespruit village 4 years prior; It was first known as the Code of Practice for Mine Residue Deposits (SABS 0286:1998) which later renamed to SANS 10286 (Dixon-Hardy & Engels, 2007). This guideline was also recommended as one of the resourceful documents by the MAC guideline.

The purpose of this guide was to talk about concerns about structure-related issues and preventative measures. The following are the suggested principles in the guideline:

1. Continual management: Emphasized for on-going process
2. The minimization of waste and the impacts of waste: Reduce waste production and its footprint
3. Precautionary principle: Use a conservative risk analysis
4. Internalization of costs: Cost description should be true to all levels of risk

5. Assessment of the full cycle of implications: Waste management should be considered throughout the whole mine cycle even after closure.

Physical copy purchase of this guideline is a bit complicated especially during the 2020 pandemic. Therefore, limited information was collected.

2.2.6 United Nations Environmental Program (UNEP) and International Council on Mining and the Environment (ICME)

Teamwork between UNEP and ICME started when they organized the tailings management workshop in 1997 and 1998. They didn't necessarily publish an independent guideline, but they published a tailings management examples from around the world in 1998 (ICME/UNEP, 1998) to present sites that were managing their TSF properly at that time. It talked about case studies in the environmental management system (EMS), design and operation, and preparedness in the case of an emergency. Some quality assurance indicator suggested frequent recording of:

- Water content consistency and input particle size distribution,
- Decant water volume and quantity of input material,
- Rainfall and evaporation,
- Freeboard or water level.

The first couple of chapters shows an agreement of tailings dam design guideline between the two organizations and other organizations well known in the mining industry such as ICOLD, CDA, and USCOLD. Thus, this publication seconds the suggested parameters listed in those standards.

UNEP itself was working closely with ICOLD where they assisted the creation and publication of the bulletin 106, A Guide to Tailings Dams and Impoundments – Design, Construction, Use and Rehabilitation. Possible inspection and monitoring of parameters prone to failure are listed in Table 1 (ICOLD, 1996a) inside the bulletin. Below are the items that can be visually inspected:

- Freeboard,
- Seepage,
- Erosion on slope and toe,
- Settlement.

A plus point of this document is the remedial action that can be applied directly to prevent or prolong issues coming from the parameters above. Besides, it recommends a list of important things to consider when planning on monitoring and surveillance of tailings dam after closure.

2.2.7 International Organization for Standardization (ISO)

ISO is widely known as the extra layer of credibility companies want to achieve to show their commitment to safety and/or quality. The technical committee (TC) within ISO specializes in mining is the ISO/TC 82 which cover the standardization such as:

- Specification on specialized mining equipment for surface and underground operations,
- Best practices in the presentation of mine survey plans and drawings,
- Mineral reserve calculation methods,
- Management of mine reclamation,

- Design of structures for the mining industry,
- Special refuge/rescue chambers,
- Shaft boring machines.

It is worth mentioning that ISO has a special subcommittee dedicated only to mine closure and reclamation management called ISO/TC 82/SC 7. They are currently in the process of developing 4 standards in this area. On the other hand, there are 49 published ISO standards especially for mining within the 7 areas above. However, the common certifications in the organization's best practices of managing risk, quality, and environment are ISO 9000, ISO 14000, and ISO 31000 (Clarkson & Williams, 2019). These standards are also listed in the MAC guideline as great sources to develop site-specific OMS manual.

The ISO 9000 family addresses criteria ensuring the quality of the management system. Tailings facility management constantly come up in multiple tailings dam guideline, so this certification ensures proper management of the dam operation. There are three standards variation in this family:

- ISO 9000:2015 – Fundamentals and vocabulary
- ISO 9001:2015 – Quality management systems – Requirements
- ISO 9004:2018 – Quality of an organization – Guidance to achieve sustained success

The ISO 9000:2015 provides some vocabulary to apply as the foundation of the monitoring system was defined. Monitoring is about "determining the status of a system, a process, a product, a service, or an activity." This definition is fitting with what we're trying to accomplish in terms of detecting how stable the tailings dam is acting. Additionally, when we look at the term inspection is about the consistency of the design specification.

On the other hand, ISO 14000 is an environmental management practice. The certification is highly sought after because the tailings dam is closely related to the environment. This certification is voluntary, but it increases the credibility of the site to show that they are environmentally responsible. Listed below are the published standards in this family:

- ISO 14001:2015 – Requirements with guidance for use
- ISO 14002-1:2019 – Guidelines for using ISO 14001 to address environmental aspects and conditions within an environmental topic area – Part 1: General
- ISO 14004:2016 – General guidelines on implementation
- ISO 14005:2019 – Guidelines for a flexible approach to phased implementation
- ISO 14006:2020 – Guidelines for incorporating eco-design
- ISO 14007:2019 – Guidelines for determining environmental costs and benefits
- ISO 14008:2019 – Monetary valuation of environmental impacts and related environmental aspects

The ISO 14001:2015 provided some guidance on monitoring, measurement, analysis, and evaluation of the environmental performance. ‘The method used by the organization to monitor and measure, analyze, and evaluate should be defined in the environmental management system, in order to ensure that:

a) The timing of monitoring and measurement is coordinated with the need for analysis and evaluation results;

b) The results of monitoring and measurement are reliable, reproducible, and traceable;

c) The analysis and evaluation are reliable and reproducible, and enable the organization to report trends.’

Reliability and reproducible are some major components when working with UAV, thus the standard is giving a proper foundation for visual inspection with image processing.

Finally is the ISO 31000 family for risk management. Constant optimization takes major part across any field and when we look at the mining industry we can almost predict that managing risk is a part of daily effort. Better risk management will allow the stakeholders to be at ease with the project. Three standards included in this family are:

- ISO 31000:2018 – Principles and Guidelines on Implementation
- ISO/IEC 31013:2009 – Risk Management - Risk Assessment Techniques
- ISO Guide 73:2009 – Risk Management – Vocabulary

The risk involved with tailings dam failure is very significant financially; therefore, ‘risk treatment options given in ISO 31000:2009 include:

a) Avoiding the risk by deciding not to start or continue with the activity that gives rise to the risk;

b) Taking or increasing the risk to pursue an opportunity;

c) Removing the risk sources;

d) Changing the likelihood;

e) Changing the consequences;

f) Sharing the risk with another party or parties; and

g) Retaining the risk by informed decision.'

TSF monitoring is a way of detecting the source of risk, thus it can support point *(c)* above. Keep in mind that most of the other tailings dam guidelines do use ISO 31000 as an essential framework in creating their risk management program.

2.2.8 Federal Guidelines for Dam Safety – FEMA

FEMA is a general guideline for all types of dams in the United States especially used by federal agencies. The agency has ten regional offices where each office is responsible for multiple states. The guide is supposed to provide a basic principle for the dams but each site is encouraged to have their site-specific practices based on their size, potential hazard, and complexity. FEMA guideline is subjected to facilities owned by the government, but the hope is to create such standard that can encourage the application of these practices by the private sector.

Table 5: Inspection types for dam structure. Adapted from FEMA, 2004

	Informal	**Intermediate**	**Formal and Special**
Frequency	As regular as possible	Annual	Every 5 years
Assigned to	Dam operator	Qualified engineers	Licensed professional engineer
What to detect	Evidence or changes in leakage, erosion, sinkholes, boils, seepage, slope stability, undue settlement, displacement, tilting, cracking, deterioration, and drains and relief walls performances.	A thorough check of items from the informal check.	Structure compliance with accepted design and practices.

The guideline was created to reduce the risk of dam failure. It provided recommendations on organization management, site investigation, and design, construction, as well as operation and maintenance. Three types of inspection proposed in the document such as informal, intermediate, and formal & special. Table 5 shows the detailed description of each type. No special section was given for tailings dam only, but this applies to earthen embankment as well.

2.3 Visual Parameters

This section of the thesis will be focused on explaining the important parameters to be monitored in the tailings dam impoundment suggested by the guidelines. After examination of the guides, some parameters are shown to be the common denominator, and the others are based on the level of detail each guide was constructed. Any introduction of instrumentation within the dam could alter the material around it, so visual inspections are highly encouraged. However, not all parameters are observable with eyes. The parameters suggested are vegetation, soil moisture, tension crack or holes, deformation and displacement, seepage or leakage, freeboard, beach width and distance, erosion, and decant pond. The thesis background explained this study is mainly related to erosion by water, but it is important to have a general understanding of other visual parameters as well.

2.3.1 Vegetation

Plants, trees, or anything that can grow is the collective component of the vegetation parameter. Tailings dam vegetation would usually take people's minds to dam reclamation. Revegetation is the most common way of stabilizing any reclaimed tailings dam to avid erosion (Vick, 1983). However, an aspect of maintaining an active TSF structure is through moving vegetation to avoid spillway blockage or establishing vegetation cover on the dam to avoid erosion (CDA, 2013). ANCOLD, ICOLD, and CDA guidelines are suggesting visual inspection of vegetation in and around the dam area. The types of monitored vegetation are related to the common flora in the area of TSF. The SME Mining Engineering Handbook (2011) suggested vegetation as one of the attributes to be analyzed during site characterization because of this.

Though suggested by multiple guidelines, it's helpful to see why vegetation should be monitored. ICOLD bulletin 158 suggested visual vegetation inspections on the downstream face, dam crest, and upstream face (when accessible). This bulletin and Fell et al. (1992a) tied the overgrowth on the dam to seepage detection or excessive capillarity. CDA (2013), MAC (2019b), and Fell et al. (1992a) also used this approach as a part of the maintenance program. This applies when growth is detected on spillways or outlet channels for it can block the water discharge or the kind of overgrowth that distracts the monitoring equipment. The blockage of water discharge can lead to serious failure mechanisms such as overtopping. Keep in mind that this clogging is one of the issues that can lead to overtopping. Also, the obstruction of equipment can lead to reading errors. Logically speaking, the presence of vegetation on an active TSF should raise a red flag. Technical Bulletin 2 of the CDA guide (2007) uses the lushness of vegetation to inspect any detected anomalies related to distress symptoms or maintenance.

Based on the previous clause, the main cause of vegetation growth is water presence. The possibility of blocking seed flown into the site is very small. Thus it can flourish when there's water seepage onto the dam wall. Also, nutrients will support plant growth, so supplies can come from leaking water. On the other hand, the same leaked water can disturb the mineral supply causing the lack of vegetation.

The visual monitoring of vegetation is closely related to the post-mining operation. Sites would usually pay less attention to vegetation while TSF is active. When a site does pay attention to vegetation, it would usually through manual visual monitoring by the dam personnel. A study was done by Russel Schimmer (2008), a Ph.D. candidate at the University of Connecticut, applying the inverse of vegetation detection. Schimmer's literature research found that copper mill tailings contain three main characteristics such as non-organic environment, homogeneous grain size, and wetness. He utilized the remote sensing GIS method to detect the active copper TSF area in Arizona through the combination of these three components. The NDTI (normalized difference tailings index) threshold was modeled on the normalized difference vegetation index (NDVI). This method came out positive and effective when tested since it was able to identify and distinguish 17 mine-tailings features. This study does not use the method to detect possible instability events, but it can be expanded further.

2.3.2 Soil Moisture / Decant Pond

Soil moisture in the mining industry is best known as moisture content. The moisture content of tailings is dependent on its location within the tailings continuum chart (Figure 3). ANCOD's definition of moisture content is "mass of evaporable water as a percentage of the mass of solids" (2019). The majority of TSF in the United States employs thickened or slurry tailings type. Therefore, good water evaporation is required to ensure proper material settlement. These two tailings types consist of large water quantity, thus will produce a decant pond on the surface. Decant pond is a pool of water on the tailings surface where tailings water and stormwater are collected (ANCOLD, 2019). Figure 11 shows an aerial image of a tailings impoundment where its decant pond is easily identifiable. The water collected is commonly recycled and reuse for the operation.

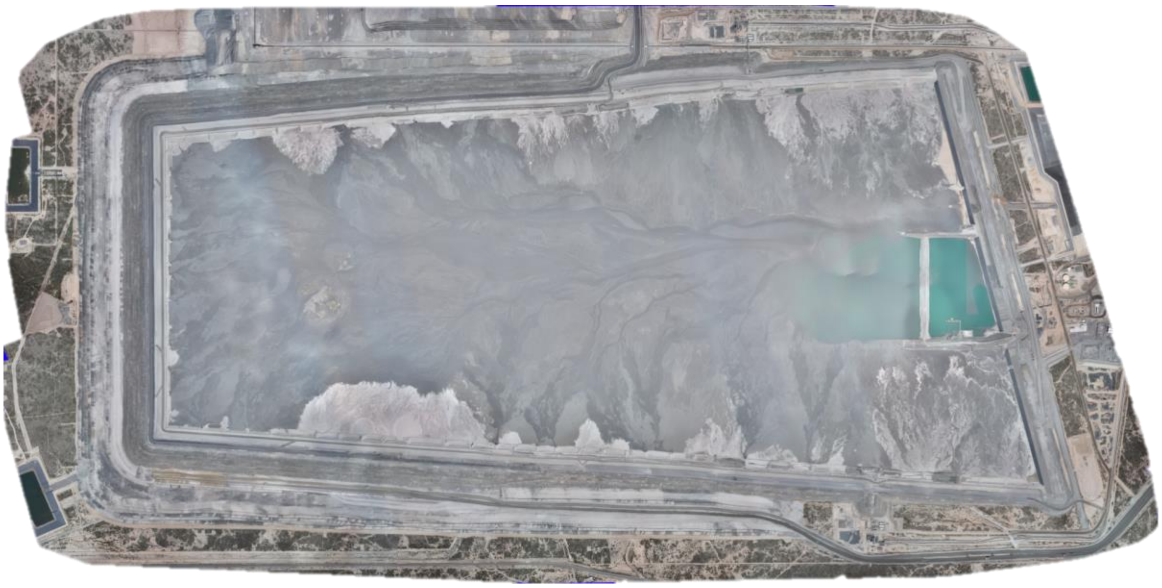


Figure 11: Aerial image of a tailings dam in Mexico. (PenasquitoMine, 2020)

The extent of moisture around the pond is related to the beaching of material after discharge. Evaporation, site temperature, and permeability are also within the variable. Furthermore, the location and allowable size of the decant pond were determined during the design process. It ties back into the chosen control method of a floating barge with a pump or a decant tower.

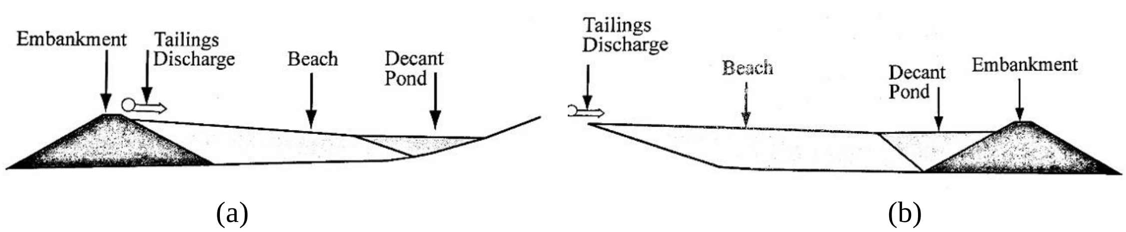


Figure 12: Two discharge directions of tailings. Upslope discharge (a) and downslope discharge (b) ANCOLD, 2019

There are two material discharging directions recorded within ANCOLD such as downslope and upslope discharge. Figure 12 shows how to differentiate them visually to the location of the embankment. Upslope is the common setup used in the industry. It is favorable because it reduces the risk of seepage and high phreatic surface (ANCOLD, 2019). The impoundment shown in Figure 11 is employing upslope and floating barge for water control.

Water location and quantity are some of the influential factors in tailings dam stability. MAC and ANCOLD suggested frequent inspection of this parameter. The monitoring of pond quantity is important for water balance purposes and freeboard availability. Pond location monitoring is related to the pump or decants tower location for the water balance requirement. Steven Vick also described how the location of the pond relative to the embankment crest as one of the factors that influence the phreatic surface location.

The visual monitoring of soil moisture and/or decant pond are getting advanced. A test was looking at a way of predicting the moisture content of tailings via thermal remote sensing. The researcher was able to quantify the change of colors to the change in moisture (Zwissler et al., 2017). This method was applied for a small laboratory-scale test, but it does have the potential to be extended into the full TFS scale. On the other hand, the monitoring of pond quantity and location was advanced by NewFields, a consulting company specialized in the design and survey of tailings impoundments. They have been using UAV and USV (unmanned surface vehicles) to survey the extent of the pond and the volume of water collected. It has been giving them accurate data that helped in optimizing the operation (Johnson et al., 2016).

2.3.3 Tension Crack

TSFs are commonly built as earthen embankment. Tension cracks are prone to develop on this kind of structure. They are associated with the soil mechanic properties of the dike. This parameter is different from the cracks created when water evaporated from the dam surface. Emergency preparedness documents are supposed to give guidelines on how to handle the situation when this occurs. Most of the time cracks are showing signs of walls strength loss.

Cracks can be developed through many events. A seismic event is one of the many causes that can develop cracks on the walls. Safety analysis at the beginning of the design process; however, the strength of future seismic load can only be predicted based on historical trends. There is no precise way of knowing the precise magnitude of the earthquake that could occur. Furthermore, two other common causes for cracking in embankment are differential material settlement and hydraulic fracturing (CDA, 2013). Slope stability analysis taking seismic assessment into account was usually done with the factor of safety (Fos), but the level of conservatism is dependent on each site. Preventive measures for crack development are planned during this stage which carried into the operational stage. Bulletin 181 added that cracking can be developed in the case of differential settlements (ICOLD, 2019)

The majority of dam guidelines mentioned the importance of crack monitoring, for it serves as a major sign of failure. Bulletin 106 from ICOLD connected the presence of tension cracks on top of the crest as a sign of instability due to shear failure (1996). New cracks development can cause further seepage problem that directly impacts the dam safety (ICOLD, 2018). A great number of failures recorded within ICOLD Bulletin 180 found cracks development as another element that leads to failure. A failure example from The Bafokeng mine in South Africa where it failed when seepage turned to internal piping when it found a crack on the dam wall.

At this point, monitoring of tension crack has not been too advanced. One way of detecting hydraulic fracturing is via piezometer level reading. However, the guides mentioned that instrumentation to serve only as an aid to visual inspections. There is no visual detection aid in the market at this point.

2.3.4 Deformation and Displacement

Movement of dam walls is another parameter as crucial as cracks detection. It is shown through the monitoring suggestion by most of the guidelines. These parameters are related to the stability of walls, contained materials, and dam foundation. Its inevitability of occurring left the designer with all kinds of analysis to lower the risk of failure. The factor of safety is also one of the engineering parameters utilized to create an acceptable range. Furthermore, stability analyses were done during the design process where multiple scenarios were analyzed to predict the risk involved with the TSF.

The MAC guideline provided several levels of displacement and the level of risk it possesses. Note that this was designed to serve as a guideline to then expanded for any specific site. There are four levels of risk such as acceptable situation, low risk, moderate risk, and high-risk situation. It is acceptable when deformation or displacement is not visible or within the designed range. When it started to become visible and exceed the designed limit, then it gets into low risk. Moderate is when toe have displaced in the form of sloughing, and movement exceeded historical data. Lastly, sloughing occurred and traveled more than 3 meters from the original location. Furthermore, it is better to detect it as soon as possible when less risk involved.

Some possible causes of displacement and deformation are earthquake, settlement, and traffic (if applicable). Earthquakes possess the highest risk of movement due to our inability to prevent nor estimate its time and magnitude. The analyses suggested by the guides involved the strength of material sustaining different loads. In the same way, proper tailings deposition could help in controlling how the material settles. It is not ideal to have traffic on the dam surface nor walls, but extra precaution should be given or possibly avoid it altogether.

As previously mentioned, there are multiple causes of deformation and displacement, so sites can only detect and monitor them. Bulletin 158 (2018) says that "displacement and deformations of the dam body are critical indicators of dam stability." The inspection needs to keep track of the location, direction, and geometry of movement. Proper personnel should be notified immediately when a drastic change was identified thus allowing quick action to be taken. Fractures created through these kinds of activities are the leading reasons for foundational failures (Lyu et al., 2019).

There are multiple ways available to monitor this parameter properly. Deformation and displacement deal with an extreme relationship with the dam foundation, but there is no way to visually inspect the foundation. Bulletin 158 suggested the use of cameras, thick gauges, hand levels, measuring tapes, etc. to aid field inspections. A well-known instrument for this parameter is an inclinometer. A proper installment in the right places could alert the personnel. On top of that, the current technologies have allowed mines to utilize LiDAR data to detect any changes. A study shows the advantage of this method especially for a small mining operation and developing countries (Lumbroso et al., 2019). However, this usually takes a longer report period due to the limited rotational capacity of the satellite. To combat this issue, some mines have been taking advantage of drones to survey the mines for quick data acquisition. It is very easy to compare the latest data and the one before to measure new movement. An issue would be the difficulty in realizing a slow trend going on. This requires proper analysis by experienced personnel.

2.3.5 Seepage or Leakage

Water is a material that can always seep its way through small cracks or porous material. When this path is established, a wet spot can be easily identified on the dam wall. Most tailings dam guideline highly suggests proper monitoring of seepage. A concise definition in CDA of seepage is when "contaminated fluid escapes to the natural environment" (2013). Similar to deformation and displacement, seepage is inevitable for an embankment dam, so it can only be controlled. Furthermore, the potential development of seepage is not only through the embankment, but also the foundation and floor of the entire structure (ANCOLD, 2019).

The cause of seepage is simple yet tricky. Two laws that can explain elementary reasons behind seepage. The first one is the law of osmosis which is a spontaneous event of selective molecule transfer through a permeable membrane. In this case, the dam acts as the permeable membrane. ANCOLD (2019) guide says that the second law is how fluid tends to flow from higher pressure to lower pressure. Build up pressure within the dam is the location of high pressure, and the other side of the dam has lower pressure (atmospheric). Therefore, the combination of these two natural phenomena is the main drive of seepage. It could get worse when cracks are involved in the equation which provides the least resistant path for water.

The most sensitive issue on an impoundment is seepage (Vick, 1983) because the liquid inside the dam is contaminated with reagents, metals, and materials that are dangerous to the environment. A recent comprehensive review of tailings dam failures from around the world determined that seepage is one of the main causes (Lyu et al., 2019). Data shown in Figure 6 from the previous chapter are from the same database used in the review paper. Also, the best way to qualitatively measure dam performance is by looking at the seepage data (Fell et al., 1992). All of the tailings dam guidelines listed seepage as one of the indicators that need to be visually inspected regularly. Seepage left to develop further will end up to internal piping. Therefore, the site should have proper measurement and observation of seepage location, quality, quantity, etc. The most famous failure caused by seepage happened back in 1974 at the Bafokeng, South Africa where 12 lives lost and trailed 45 km of material downstream (WISE, 2016).

An important step of TSF design is water management especially maintaining the water balance. Even though seepage might not contribute significantly to the calculation, the concern comes to the environmental impact. Bulletin 106 argued the importance of seepage collection pond as an alternative (ICOLD, 1996). This will allow for easy management and amount tracking. Suggestions given by guidelines in controlling seepage are through adding barriers between tailings and walls, creating a return system, or utilizing liners (Vick, 1983).

Due to the certainty of seepage occurrence, many studies were mostly on finding ways to better predict the quality and quantity of seepage. However, the literature showed a lack of studies developed in monitoring and detecting this parameter. The common monitoring instrumentation is through the installation of multiple piezometers around the TSF. The relationship between the phreatic line and seepage was briefly explained earlier. A study was done at three tailings dam in Sweden (the Kiruna, Aitik, and Kristineberg) back in 2015 was using the geoelectrical method to monitor potential seepage locations. Two methods were studied including self-potential (SP) and electrical resistivity. SP method was looking at finding locations with high electrical streaming potential since water followed the same principle of flowing from high to low potential places. On the other hand, the electrical resistivity method was found to better serve to detect water level, dam core, dam material type, inhomogeneity, and saturation (Mainali et al., 2015). A famous analytical method that relates the saturation line with seepage is Darcy's Law, thus saturation line monitoring can boost understanding of seepage monitoring. A study proposing an on-line monitoring method to connect the in-field instrument and central data monitoring through optical signal, disclosed the possibility of real-time monitoring (Li et al., 2011). However, this study did not include a field test that can support the methodology. It looked at the methodology of applying vibrating wire technology that can detect pore pressure change based on the wire tension. The issue with these methods is the use of a ground-disturbing instrument which impact the dam stability.

2.3.6 Freeboard

The Australian guideline, ANCOLD, a general definition of freeboard is the distance between the critical designed water level and the current water level in the dam. This distance is profoundly related to the location of the dam facility because extra measures should be placed to count for extreme conditions as a storm or wet season. Therefore, the total freeboard is a bit more complex to calculate. Figure 13 illustrates possible water levels subjected for different purposes of analysis.

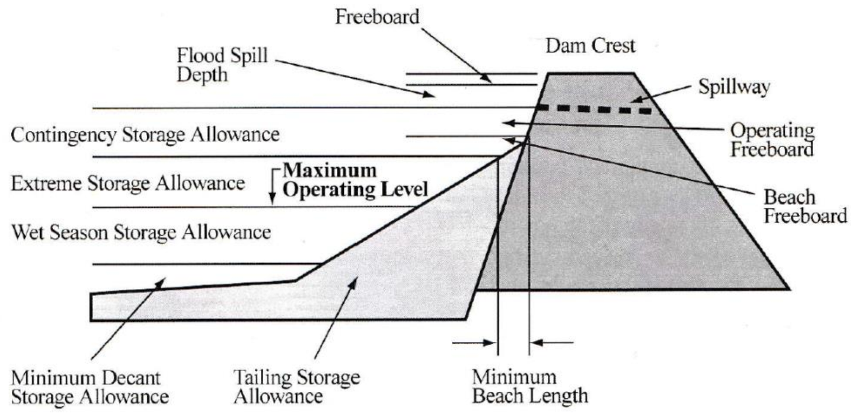


Figure 13: Freeboard design parameters in a typical dam impoundment. The sketch was taken directly from the design guideline. (ANCOLD, 2019)

A detailed explanation of each element of freeboard criteria is presented in the ANCOLD guideline; however, some of the element worth mentioned and defined from the figure are:

- Minimum decant storage allowance: Minimum amount of water expected to be held within the dam to achieve the required discharge condition.
- Wet season storage allowance: The water volume allowed during the wet season that includes input from rainfall and water from processing.
- Operational freeboard: The distance between the crest and the top of the tailings material.
- Maximum operating level: The highest extent where the water level can rise under normal conditions before the activation of the site's emergency plan.

Freeboard distances are giving safe ranges of water level. CDA recorded that overtopping failure would usually start with water going over the dam crest, so it's very important to not only below the maximum level but also above the minimum recommended level after discharged (CDA, 2013). Figure 6 reveals overtopping as the highest cause of failure, so freeboard monitoring shows a high potential of preventing this failure mode.

The common way of freeboard monitoring is through a regular survey and visual inspection. Mines are starting to employ UAV and USV to aid this process similar to the decant pond monitoring. The paper from NewFields mentions survey advantages when these technologies were complimented together. The monitoring is advised to be more regular in the case of high precipitation or possible storm occurrence.

2.3.7 Beach Width and Distance

Almost all of the reviewed guidelines recommended monitoring of the beach width and distance. Beach development is based on the material segregation process as it travels away from the discharge point(s) (see Figure 12). Gravity will automatically help this grading process where particle distribution is reduced as it travels further. It is common to find the finer particles accumulated below the decant pond. Furthermore, the resulting width is controlled by the amount of discharge point if multiple points employed.

The beach width and distance design are tied to many different aspects. Tailings rheology, temperature, required beach angle, deposition rate, etc. Rheology is crucial, especially for higher solid concentration tailings (ANCOLD, 2019). ICOLD Bulletin 181 collected beach slope data from around the world and plot its correlation to the beach length (see Figure 14). This study proved how beach length is the inverse of the beach slope as expected. The concave shape is also predicted since the coarser particle tends to pile into a steeper slope. Guidelines suggested the overall beach slope to be within the range of 1-4% for uniform material distribution.

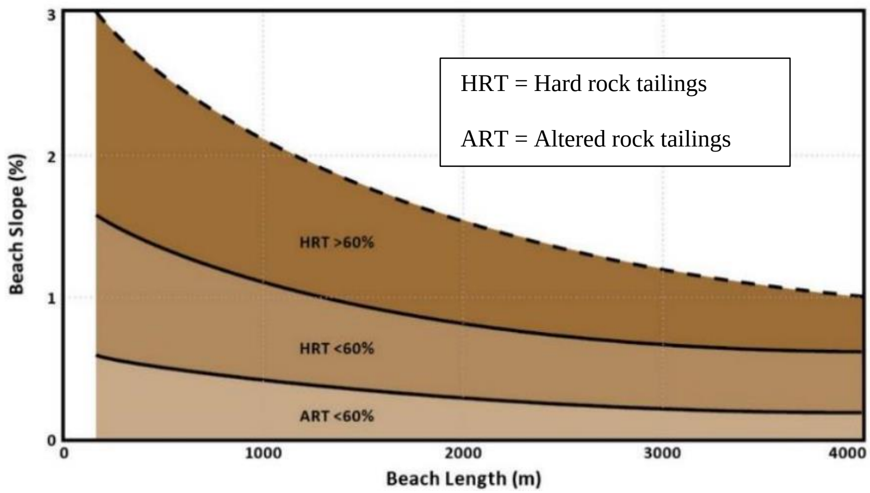


Figure 14: The relationship between beach length and slope based on different tailings type. (ICOLD, 2019)

Material segregation, settlement, and water management are some of the closely watched parameters. The MAC guideline (2019b) suggested the control of beach angle for better tailings placement, and the control of beach width for water management. Due to the segregation nature of tailings previously mentioned, the beach angle is especially crucial for the upstream raise method. The distance should be long enough to create more surface area for water evaporation since the next dike cannot be constructed on a wet surface. A delayed material settlement will create dike collapsing shown by the development of tension crack. Another risk coming from incorrect beaching is dusting. A large amount of mine operation is located in an arid area, so these small particles need to be suppressed. This issue is why the reclaim pond location and extent are also monitored.

The monitoring of beaching is crucial to ensure conformity between field performance and design criteria. Visual inspection is highly recommended to ensure proper material distribution. On the other hand, manual calculation of beach distance is discouraged if it requires stepping inside of the dam. Therefore mines have also utilized UAV and LiDAR applications to obtain better aerial surveys and views. A computer simulation study was done based on TSF in Arizona employing drones. It correlates the design FoS and the current beach distance to calculate the critical distances for safe operation. They simulated different weather conditions and found its usefulness in checking the dam performance (Jeong & Kim, 2019). This study was for upstream TSF, thus further study should be done to expand this application. The approach serves as a good foundation for future expansion of precise monitoring and continual risk analysis.

2.3.8 Erosion

The natural process of erosion will always take place on any embankment dam. Erosion itself is the process of soil removal and getting transported elsewhere. Note that internal erosion or piping is different from this topic since it is hard to visually inspect. The erosion process monitoring was recommended by the majority of guidelines. External erosion is considered the main topic which is also different from the weathering process. ICOLD Bulletin 158 (2018) identified weathering as alternating actions from drying to wetting or freeze to thaw.

Erosion can occur via constant impact with the wind, water, or other natural agents. Wind and water erosions are the two common occurrences in tailings dams. Typical forms of water erosion are rills, gullies, and sheets (see Figure 15). Rill erosion is presented as branch-like lines on the dam wall. Gullies are the way deeper advancement of rills. Sheet erosion removes a wide area of soil at once. On the other hand, wind erosion can look similar to rills but differentiable by the ripple effects created. Wind can only pick up small particles, so it is less likely developed on TSF. Moreover, factors influencing erosion are precipitation, soil strength, length, slope angle, exposure time, etc.

Figure 15: Three common types of water erosion. (Bashir et al., 2017)

Erosion was shown in Figure 6 as one of the many causes of failure. ICOLD (1996b) explains that “the slow deteriorative processes or progressive degradation may lead to overall failure and may have severe adverse long-term environmental consequences.” This statement applies to the erosion process. Erosion is causing dam material to be transported somewhere else, thus reducing the strength of the designed walls. Early signs or progression discovery through proper monitoring is important. This will allow proper repair actions as soon as possible. Extra precaution is needed especially after a heavy rain season. The steepening event of toe erosion can lead to rotational slips (ICOLD, 2001). Occurrences of these events are recommended to be considered during the initial engineering analysis (Lupo & Scharnhorst, 2019). Protection against erosion during the active period is less desirable for most mining operations. Documents commonly suggest cover utilization when going into the reclamation step for a lasting effect.

Erosions are easily identifiable visually. It is time consuming especially for large impoundments. The detection of erosion for agricultural purposes is advancing way rapidly than in the mining industry. LiDAR and aerial images are mostly used after site reclamation (Slingerland et al., 2018). Currently, there is no special instrumentation that can aid visual inspection. Therefore, adapting methods from agriculture would be helpful. Mines can take advantage of the high-quality aerial images from the mine survey to alleviate erosion detection.

2.4 Monitoring Systems

When mentioning systems, it covers multiple instruments and layers of monitoring. ISO 9000:2015 defined system as the "set of interrelated or interacting elements." The system itself will be site-specific thus each might have a slight composition difference. Performance-based monitoring is a system where it seeks possible hazards, possible failure mechanisms, signs to look for, and how to detect it (CDA, 2013). Several documents included a guideline on how to build a proper system. A surveillance program is described to consist of multiple performance monitoring such as (CDA, 2013):

- "Comparison between the actual and design performance to identify deviations
- Detection of changes in performance or the development of hazardous conditions
- Confirmation that reservoir operations are following the dam safety requirements
- Confirmation of adequate maintenance is being carried out."

A common requirement of a monitoring system is its ability to be carried out continually. Items related to stability could resort to FoS as the assessment basis.

A challenge with monitoring is the time constraint. Warning time determined from the surveillance system can range from days, months, years, even hours or minutes (CDA, 2013). The failure of Mount Polley in Canada was extreme for no warning sign found.

Therefore, real-time monitoring is favorable for even better operation. There have been many studies done in the past to test different monitoring methods for tailings impoundment. A summary of these studies is listed in Table 6 below.

2.1 Remote Sensing and Machine Learning in Mining

Two main remote sensing utilizations in the mining operation are mine mapping and geotechnical monitoring. The SME handbook listed some instrumentation for geotechnical such as satellite InSAR (Interferomagnetic synthetic aperture radar), radar, and LiDAR (Light Detection and Ranging) & Photogrammetry (Frith & Colwell, 2011). Similarly, topographic survey methods with remote sensing are aerial and terrestrial photogrammetry, GPS, and laser scan (Jarosz, 2011). Data collected through these means can be presented in the format of high-quality images, point cloud, digital elevation model (DEM), photogrammetry, etc. Recent studies showed that the same instruments can also assist tailings dam monitoring for moisture content (Zwissler et al., 2017), beach distance (Jeong & Kim, 2019), erosion (Slingerland et al., 2018), and displacement (Gama et al., 2019; Lumbroso et al., 2019; Rauhala et al., 2017). However, Clarkson and Willams (2019) found that only 35% of the 25 expert tailings practitioners interviewed implemented slope stability radar on their TSF.

Machine learning in mining, as previously mentioned, is not as advanced as the other fields. To simply put it, the potential applications are gases and hazard detection can lead to an early warning, increase the efficiency of production and sampling process, selective grinding application, etc (Hyder et al., 2019). Unfortunately, most mining technology suppliers have only been developing machine learning for equipment (i.e., truck automation) (Lee et al., 2019). The extent of development was tailings dam detection through satellite images (Ferreira et al., 2020; Schimmer, 2008). However, the engineers involved in a machine learning workshop realized that machine learning application to predict tailings TSF failure is necessary, especially after the recent failure in Burmadinho (Leonida, 2019).

In any new technology, there will be advantages and disadvantages. The downside would be people's concern about losing their job to technology. Also, there will be risk taken in more capital cost to purchase the instrument, software, and personnel training. However, this monitoring revolution should be considered from its safety aspect to the dam personnel, surrounding town, environment, and the value-added to improve efficiency and productivity of the company (Hyder et al., 2019).

Table 6: Various studies on tailings dam monitoring.

Author(s) and year	Article Title and Year	Case study	Monitoring method	Parameters monitored	Type of research	Description of work	Scale of study
(Zwissler et al., 2017)	Thermal Remote Sensing for Moisture Content Monitoring of Mine Tailings: Laboratory Study (2017)	Tailings samples are from two North American Iron mines (Michigan and Minnesota)	Thermal Remote Sensor	Moisture Content	Academic	Variables measured are mass, penetration depth, spectral reference, atmospheric temp., humidity, and thermal images. The recorded gravimetric moisture content and penetration depth plot show an exponential relationship with the different coefficient for each site. Regression models are created where sample temperature and atmospheric humidity are the most significant parameters.	Laboratory -scale test
(Jeong & Kim, 2019)	A Case Study: Determination of the Optimal Tailings Beach Distance as a Guideline for Safe Water Management in an Upstream TSF (2019)	A mine in southern Arizona (undisclosed)	UAV (drone)	Beach Distance	Academic	A digital model was first created from drone data. TSF uses the factor of safety as the safety measurement standard, so the authors use this value to calculate the critical beach distance ($D_{critical}$) under normal conditions. By keeping the FoS = 2.0 for $D_{critical}$, other variables are varied to simulate different weather conditions ($D_{rainfall}$ and D_{wind}). The study found an optimal safe beach distance to maintain the factor of safety requirements. Furthermore, this number is for the current geometry, so constant update should be done and this is only applicable to a well-managed	Full TSF in a computer simulation

						that features a smooth, non-undulating beach surface.	
(Mainali et al., 2015)	Tailings Dam Monitoring in Swedish Mines Using Self-Potential and Electrical Resistivity Methods (2015)	All located in Nothern Sweeden. Site 1: Kiruna (LKAB) Site 2: Aitik Site 3: Kristineberg	Geoelectrical: Self-potential (SP), Electrical Resistivity	Seepage on wall	Academic	SP method uses a streaming potential test to check the natural potential difference between soil grains. Water flows from low to high pressure, so this method can detect potential seepage locations on the wall. Tailings contain water and water is the best conductor of electricity, so saturated soil should show low resistivity thus allowing creating a map along with the selected profile on each site. Electrical resistivity can be used to detect water table location also. Both methods show great success in detecting potential seepage.	Full TSF
(Slingerland et al., 2018)	Identification and Quantification of Erosion on a Sand Tailings Dam (2018)	Athabasca Oil Sands (AOS) in Alberta, Canada	LiDAR and Aerial Photo	Erosion	Company	The objective is to investigate tailings erodibility of the site. They want to have a better understanding of future design based on the current state and test the possibility of sourcing LiDAR and aerial photos to identify and quantify erosion signs after reclamation. The in-person assessment was done before to understand the rills and gullies appearance on site. The study shows that both water and wind erosion are present. The authors then test if LiDAR and aerial photography models can	Full TSF

						be used to identify, classify, quantify, and determine the cause of erosion. Both methods have their pro and cons, but the digital stereo aerial photography was more superior in most assessments but limited when quantifying erosion.	
(Hu & Liu, 2011)	Design and Implementation of Tailings Dam Security Monitoring Systems (2011)	China	Sensors buried in tailings, GPS, and video surveillance	Saturation line, water level, internal horizontal and vertical displacements, and surface displacement	Academic and Company	The authors created software to automate streamlining data acquisition, presentation, and alert system. It shows a promising result of how this software can do such things back then. One shortcoming of this paper is the lack of result analysis to see the accuracy of these data compared to manual data.	Full TSF
(Lumbroso et al., 2019)	The Potential to Reduce Risk Posed by Tailings Dams Using Satellite-Based Information	Cajamarca, Peru	Satellite	Displacement, Deformation,	Academic and Company	The need for low cost and efficient monitoring system for developing countries and small mining operations drove the development of this system. The software of using satellite images for tailings dam monitoring is currently in the testing stage at mines in Peru. It shows great potential and where it allows broader coverage and transparency to the government and the public.	Full TSF
(Gama et al., 2019)	Advanced DINSAR Analysis on	Mariana, Brazil	Advanced Differential SAR	Deformation	Company	The satellite imaging system was studied to see its ability and feasibility in tailings dam	Full TSF

	Dam Stability Monitoring: A Case Study in Germano Mining Complex (Mariana, Brazil) with SBAS and PSI Techniques (2019)		Interferometry : SBAS and PSI			monitoring. The SBAS technique shows better detection of deformation. The use of satellite data also provides a cheaper rate compared to the installation of full ground movement equipment especially for small companies located in developing countries.	
(Rauhala et al., 2017)	UAV Remote Sensing Surveillance of a Mine Tailings Impoundment in Sub-Arctic Conditions (2017)	Laiva Mine, central Finland	Unmanned Aerial Vehicle (UAV)	Surface displacement	Academic	Four measurement campaigns were performed in a sub-arctic environment when the mine was temporarily inactive (during the summer). Stable areas around the perimeter were used as ground control points. The use of UAV greatly reduced large area concern. The displacements detected were related to a combination of tailings settlement, erosion, and possible compaction of the peat layer underneath. The resulting data measurement was accurate and can track to the decimeter range.	Full TSF
(Q. M. Li et al., 2011)	Tailings dam breach disaster on-line monitoring method and system realization (2011)	China	GPS and vibrating wire type sensor	Displacement and saturation line	Academic	This study proposed a method of creating an on-line monitoring system with GPS to detect displacement and vibrating wire sensors to find the saturation line. The methodology served as a good base to develop this system further. Data were gathered in-situ through ground	Full TSF

						instruments and transferred as an optical signal to the data monitoring and alert center. No numerical result was given since this was a proposed method only.	

CHAPTER 3 : CONVOLUTIONAL NEURAL NETWORKS

3.1 Introduction

Machine learning (ML) application itself has been around for a while. The first project related to this was called "The Summer Vision Project" back in 1966 by Massachusetts Institue of Technology. The goal was to create a system that can classify pictures based on the likeness of objects, background similarity, and chaos (Papert, 1966). However, the invention of spam mail filters in an email provider was the most famous application back in the 1990s. Machine learning itself is about creating a model for the machine (i.e., computer) to learn from a dataset. Best practices for continual learning through a closed-loop program where results are evaluated regularly (Geron, 2017). There are many different machine learning systems developed by now, but the main criteria focused on this study is supervised learning with batch and instance-based learning. Supervised learning is when data were assigned labels for different classes. Batch learning is also known as offline learning where all data are fed into the model at once instead of in pieces. Lastly, instance-based learning is when the model learns the examples by heart and use similarity measure to generalize new instances (Geron, 2017).

The technological advances accomplished through machine learning are pushing multiple fields to apply this as well. Safety is one of the main cultures in most mining companies, so continual safety quality improvement is encouraged. The ML applications in the mining industry currently are toward prospecting and exploration, exploratory and production drilling, operations, and autonomous vehicle; however there is a potential to apply it further to gas and hazard detection, production, sampling, autonomous support systems, mineral processing application, and accident analysis (Hyder et al., 2019). This research was an aspect to add to the machine learning application in hazard detection using remote sensing on tailings impoundment. Remote sensing application can fulfill OHSA's (2016) most effective point in the hierarchy of control which is elimination. Remote sensing can aid to eliminate the long in-person visual inspection of TSF and machine learning can help to detect the hazards.

Challenges in machine learning are tied to the best way to train the model and the quality of data used. Aurelien Geron (2017) in his book explained some of them such as algorithms that overfit or underfit the training data, low-quality training data, data don't represent the whole population, lack of data, or irrelevant features given. Algorithm related challenge means that it either works well with the training set but not general enough to handle new test data, or it is too simple to predict complex examples. On the other hand, data related means to feed abundant, high-quality data containing enough relevant features that represent different possible instances. All of these requirements when followed should result in a good quality model that can be generalized to different datasets. The challenge encountered in this study was the low quantity of training data. Further explanation is given in the next sub-chapter.

3.2 Computer Vision (CV)

For humans, vision is the next level of seeing something. The Merriam-Webster dictionary records the word vision as "the special sense by which the qualities of an object (such as color, luminosity, shape, and size) constituting its appearance are perceived through …" Therefore, the term computer vision is a field to extend this ability into computers (Goodfellow et al., 2016). It is known as an interdisciplinary field that branches from AI and ML (Brownlee, 2019). Images and videos serve as the input then the trained computer model would hopefully produce the appropriate output. Its combination with engineering resulted in the automation of visual inspection applied to many manufacturing facilities nowadays. Pattern recognition, image processing, and artificial intelligence are some of the many tasks of computer vision (Lamba, 2019).

The common human eyes see an image based on shapes and color that makes up an entire input. In contrast, the computer sees numbers that associate with each pixel value which translated into the color that the human eyes see (Brownlee, 2019). This pixel value will vary based on many aspects. Figure 16 presents some issues that can complicate how images can be translated. Different illumination for a computer will result in a different image value, but humans would understand that they are the same object. Thus the aim is to train computers understanding what is displayed in these images (Brownlee, 2019).

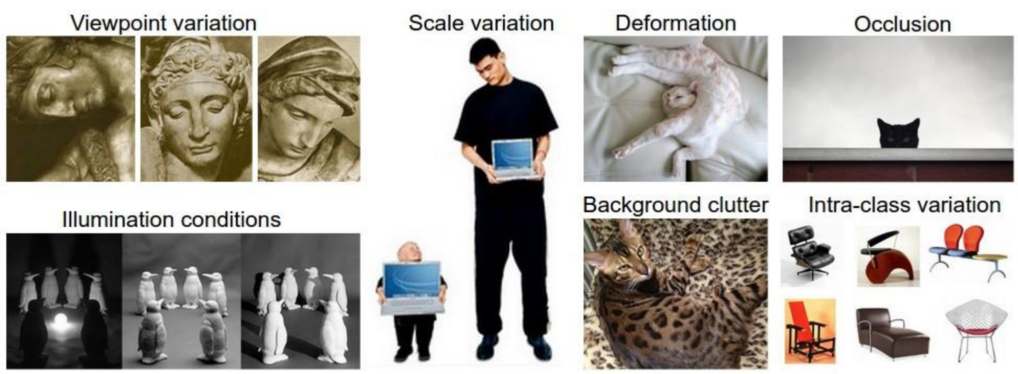


Figure 16: Possible issues that affect how computer "sees" images (Soleimany, 2019)

There are levels of granularity for computers to understand the image such as through image classification, classification with localization, object detection, semantic segmentation, and instance segmentation (Lamba, 2019). This research is focusing on semantic image segmentation which will later be explored.

3.3 Neural Networks

Machine learning is a very broad topic. The four big types of machine learning are supervised, unsupervised, semi-supervised, and reinforcement learning (Geron, 2017). The first three types differ based on the number of labeled input data, yet reinforcement learning works through applying penalties/rewards for different actions (Goodfellow et al., 2016). This study aims to classify the “rill” and “non-rill” area, so the supervised learning is selected where labels are given. A study based at the University of Nevada, Reno under the same NIOSH funded capacity building project by Winkelmaier et al. (2020) showed that Convolutional Neural Networks (CNN) served as the best feature detection algorithm for images taken with UAV. The study tested two well-known image segmentation architecture namely ENet and UNet. This research employs UNet as the main algorithm since it is proven to perform well with small datasets (Ronneberger et al., 2015).

CNN is a type of neural network. Neural Network itself is modeled after the human brain where many sets of algorithms are designed together to recognize patterns (Pathmind, n.d.). CNNs was first explored in a study about the brain’s visual cortex (Geron, 2017). It has since been known to be more straightforward and requires less preprocessing compared to traditional computer vision models (Sattarvand & Parvin, 2019). The word convolutional in the name refers to the specialized type of linear operation in the field of mathematics (Goodfellow et al., 2016).

Convolutional networks commonly consist of three stages such as convolutions, activation, and pooling (Goodfellow et al., 2016). Sattarvand and Parvin (2019) recorded Eq. 1 as the convolutional operation. It takes a 2D image *I* as the input where *K* is known as *kernel* of the convolutional *filter*.

$$s(i,j) = \sum_{n}\sum_{m} I(i-m)(j-n)K(m,n) \quad (1)$$

The output is commonly referred to as a *feature map* (Goodfellow et al., 2016). Figure 17 shows an example of 2D convolution on a sample 2D matrix. It utilizes dot products between the image and the kernel.

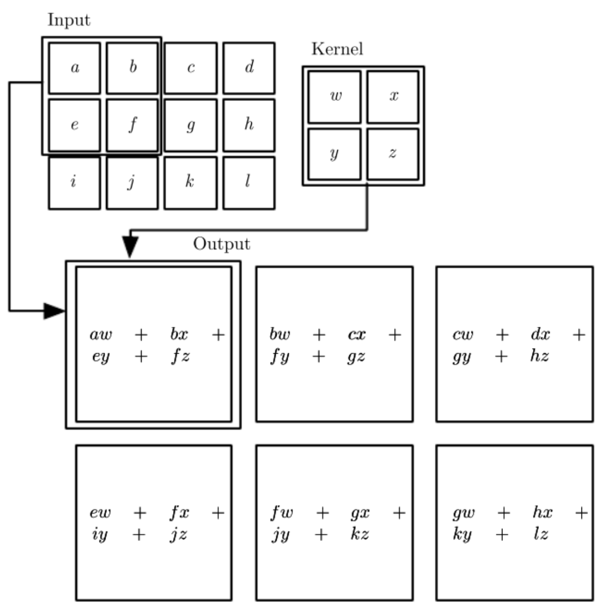


Figure 17: An example of a 2D convolution operation (Goodfellow et al., 2016)

CNN problems typically have a smaller kernel size compared to the input image. Meaningful or small features (i.e., edges) in images with thousands or millions of pixels can be detected by the typical Kernel sizes of 3×3 or 5×5 (Sattarvand & Parvin, 2019). Therefore, fewer parameters can extract useful features effectively.

The second block of CNN is nonlinear operations to achieve more sophisticated models. That operation is referred to as an *activation function*, which applied after the convolutional operation. There are some functions currently known such as CUBE, ELU, Sigmoid, ReLU, TANH, etc. The selected function will determine the generated output (Pathmind, n.d.). However, the default function in CNNs is *ReLU* or *rectified linear unit* in the form of Eq. 2 (Goodfellow et al., 2016).

$$g(z) = \max\{0, z\} \tag{2}$$

The last essential building block of CNNs is the pooling operation. It takes the resulted feature map from the activation function and replaces some values on certain locations with a summary of the nearby locations (Sattarvand & Parvin, 2019). *Max pooling* is commonly chosen which reduces the image size by half (Zhang, 2019). Smaller image size running in the network translates to computational improvement and efficient memory use. Figure 18 shows the 2D *Max pooling* operation with a filter size of 2×2 that reduces the input by a factor of 2. This example shows how it picks the highest value in each rectangular color to be carried as the output.

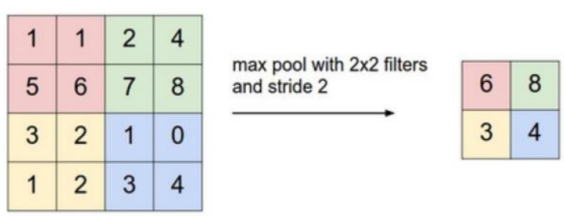


Figure 18: Example of a 2D pooling operation (Sattarvand & Parvin, 2019)

Various architecture of CNN has been developed as different combinations are tested. They all differ by the number of layers, the number of convolutional filters in each layer, and the employed pooling operations which all referred to as *hyperparameters* (Sattarvand

& Parvin, 2019). Multiple trials and errors might be necessary to find the appropriate architecture. *UNet*, *AlexNet*, *SegNet*, etc are some examples of CNN architecture. The following section consists of the architecture utilized for this research.

3.3.1 UNet for Semantic Segmentation

Out of the many options in computer vision, semantic segmentation is perceived to work effectively in the task of rills identification on tailings dam. This type of classification is based on the pixel level (Mansouri, 2019). Instance segmentation is another term typically confused with semantic segmentation. Instance segmentation is an elevated method based on semantic segmentation applied to moving data (i.e., video) where different frames represent different input images (Yang et al., 2019). Figure 19 shows an example of a semantic segmentation. Thus, it associates different pixels with a class label i.e "person" or "background" in this example. UNet is an architecture frequently used for semantic segmentation. Winkelmaier et al. (2020) proved that UNet can competently detect features from UAV data.

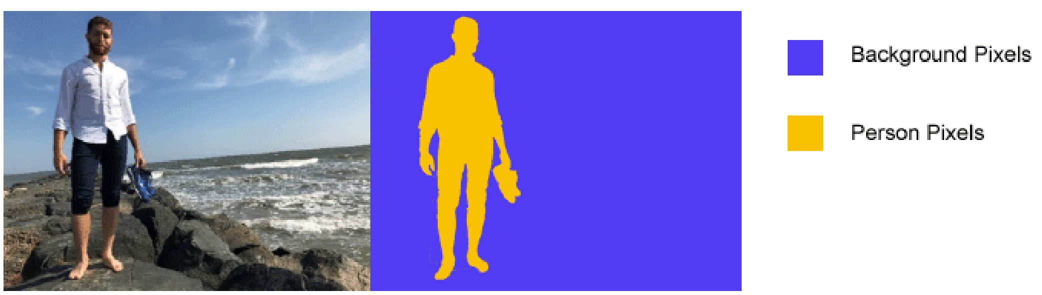


Figure 19: Semantic image segmentation (MathWorks, 2018)

The original UNet architecture is shown in Figure 20. The blue boxes each corresponds to a multi-channel feature map. The number on the lower-left of the box signifies the size of feature maps of each layer. This figure, for example, has an input size of 572×572. The second layer was produced after the convolution operation which reduced the size by 2 pixels resulting in feature maps of size 570×570). Convolutional filters of size 3×3 and 1×1 are employed throughout the network example. The number of these filters used in each layer is presented on top of the blue boxes.

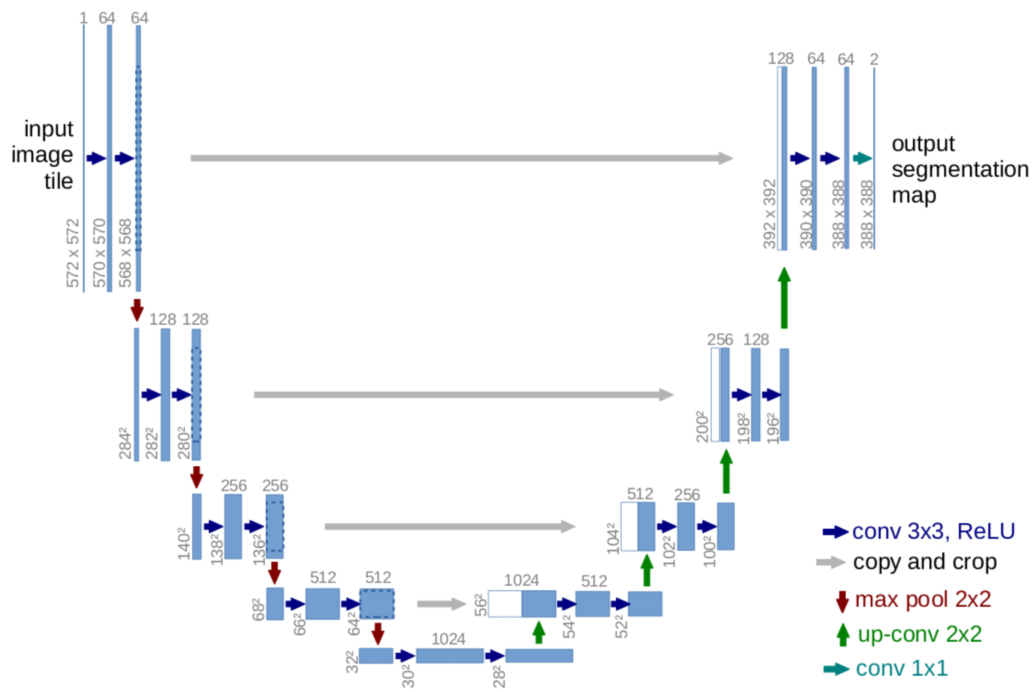


Figure 20: The original UNet architecture (Ronneberger et al., 2015)

The UNet architecture was developed back in 2015 for biomedical purposes. The network's U shape architecture as seen in Figure 20 was the lead to its name. It was an expansion of the *fully convolutional network*, and it was proven to provide more precise segmentation with very few training images (Ronneberger et al., 2015). The architecture depicts that the first half is assigned to reducing the resolution while increasing the number of filters and vice versa in the second half. This contracting and expanding path is the key to precise localization of the desired feature(s) (Ronneberger et al., 2015).

A machine learning model training generally requires multiple trial and errors. This is due to testing and adjusting hyperparameters within the model to accurately produce the desired result. Specific to UNet, the adjustable hyperparameters are learning rate (lr), dropout, L_2 regularization, weight factor for positive class loss, batch size, epochs, and image patch size. The following are abbreviated explanations of these specifications (Geron, 2017; Goodfellow et al., 2016):

- Learning rate (lr): Step size is another term used for this hyperparameter. It determines the rate of weight being updated during the model training. Researchers always found this hyperparameter as the most difficult to set because it significantly impacts the model performance. The value ranges from 1e-2 to 1e-5. The selected rate should be balanced by the batch size and number of epochs. It is recognized as the most important hyperparameter since selecting a number that is too small will stuck the process and too large will lead to quick converge into the local minima.
- Dropout rate: This hyperparameter is implemented within the layers of UNet architecture and also known as dilution. It serves as a powerful and most popular regularization method. Regularization is a strategy to reduce test error by possibly increasing the training error. It randomly 'drops' nodes, which forces the subsequent node will spread out the weight instead of putting it all in one input thus preventing overfitting. It benefits the model with limited training data. The rate determines the percentage of input dropped getting into a new unit. 0.5 is the commonly assigned value, so it means half of the input will be dropped and unable to move forward in the network.

- L_2: This too is a common regularization technique known as weight decay purposed to avoid overfitting. The value is presented by *lambda* in the Keras package. It is utilized to constrain the values of the weights and biases low making sure that the loss value is minimized as training continues.
- Weight factor: This factor is applied within the loss function selected for model training. The class imbalance between what is considered as “person” and “background” (see Figure 19: Semantic image segmentation (MathWorks, 2018)) does affect the performance of a neural net; thus, assigning larger weight to the positive class “person” will incentivize the training process toward correctly predicting the positive class to minimize the loss value. The default value is 0.5 which means both classes are considered equally.
- Batch size: It is the number of training images passed into the neural network at a time. The size typically employs the power of two sizes in 32 to 265 range. The learning rate and batch size should go hand in hand in the decision process.
- Image patch size: It is the size of how the large image input tiled to small patches. It is important to use the proper size to make sure the patch contains enough information for the model training. This size determination is based on the project and scale of the desired feature(s).

Many more hyperparameters are included within the model training process, but the ones explained above are known to help improve the quality of the UNet model. The final values adapted for this research are presented in the next chapter.

CHAPTER 4 : RILL EROSION DETECTION

4.1 Introduction

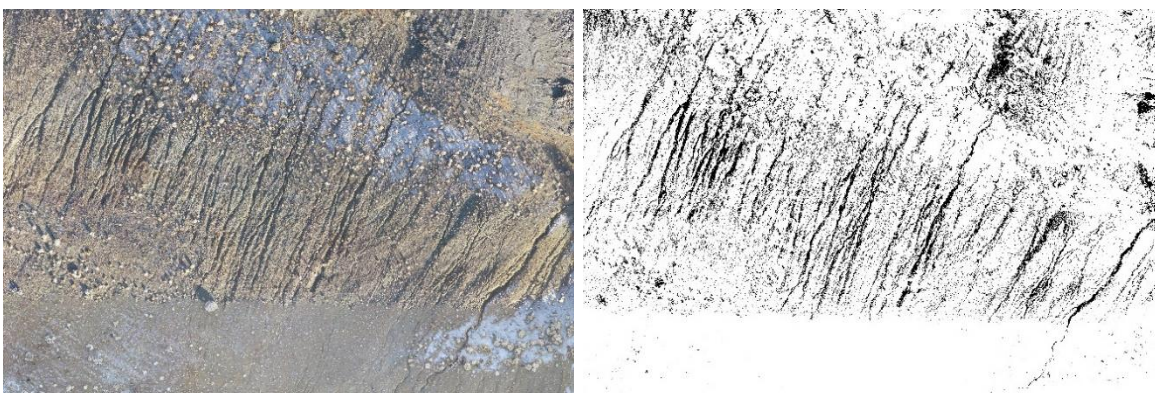
The process of building a successful machine learning model consists of multiple steps. Firstly, the researcher should look at the bigger picture and determine the main objective in creating an ML model (Geron, 2017). Rill erosion detection on TSF monitored through UAV is the purpose of the study. Then, proceed to gather the appropriate data and visualize them thus allowing the researcher to gain a better understanding of the entire dataset. Data for this research is exclusively from drone images and detailed discussion can be found later in this chapter. The next step is to prepare the data for the proper ML algorithm. Data preparation for this study was extensive which is common for image-based ML models. Furthermore, the suitable ML model can be selected or built to start training with the selected and compiled data. Rill identification model from drone images has not been developed in the literature; thus, a new model was built for the project. Finally, the promising model should be fine-tuned to accurately detect the target feature. Note that this whole system should be monitored and maintained for relevancy since new data or better algorithms can be utilized.

4.2 Data Acquisition

As described in the previous chapter, one of the important requirements to build a machine learning model is the size of the training data set. Goodfellow et al. (2016) mentioned that the increase in training data can reduce the skill required to create a good performing model. There are three approaches available to acquire data such as data discovery, data augmentation, and data generation (Roh et al., 2019). The data discovery and augmentation methods are being used in this research.

4.2.1 UAV Images

The main objective of the project is to utilize data gathered via UAVs. Initially, a test run was done on a site outside of Reno, Nevada with a flying path optimizer software recently developed by the research group (Battulwar et al., 2020). This software is not only applicable to regular terrain, but it can capture challenging terrain such as open pit mines. Out of the three considered flight areas, images coming from the second site showed the best visible rills as shown in Figure 21(a). Figure 21(b) shows the image after applying the edge detection filter in Matlab for better rill visualization.



(a) (b)

Figure 21: Rills captured in site 2 (a). Site 2 image after edge detection (b).

An advantage of UAV data is the ability to extract both images and elevation models (Digital Elevation Model-DEM). Rauhala et al. (2017) utilized this DEM data to assist their study in detecting subsidence, erosion, and settlement through a comparison of before and after points in the same location. Winkelmaier et al. (2020) created a method of mine bench detection, bench identification, and ramp identification by reviewing the gradient change captured by DEM.

Initially, the plan was to gather drone images of TSF from the partnered mines. However, existing issues at the time intercept this plan to be smoothly executed. Only several mines can provide the images, but they are not showing the number of rills desired for the model training. Only one out of three sites showed visible rills on the dam walls.

4.2.2 Google Earth Pro

The lack of data from tailings dams operations pushed the need to get creative in acquiring data. Images gathered should have good quality, come from a trustworthy source, and need to be on a plan view. Google Earth Pro was the best source option since it met these requirements. This data source was considered to fill in the gaps because Slingerland et al. (2018) proved the feasibility of erosion identification through LiDAR images. It might not as high-quality as the data gathered via UAV, but the study showed the capability of these satellite images. The selected sites for these images are in Nevada, Arizona, and New Mexico. All of these areas experience similar weather that can lead to rill erosion.

A total of seven TSF sites were recognized with visible rills through Google Earth Pro. Figure 22 shows an image example taken from a site in Arizona. It has a lot of visible rill erosion marks, thus making it easy to create the labeled mask. Mining sites are mostly located in remote areas, hence being almost impossible to obtain images with quality similar to drone data without extra cost. However, this image has 100 ft./pixel which is the closest it got without blurring the resulted image. The built-in function within the software made it easy to annotate, capture, and save these images. It also has several options that allow different map styles and resolutions. This study used data from the full-color map and the highest resolution available (4800×2886).

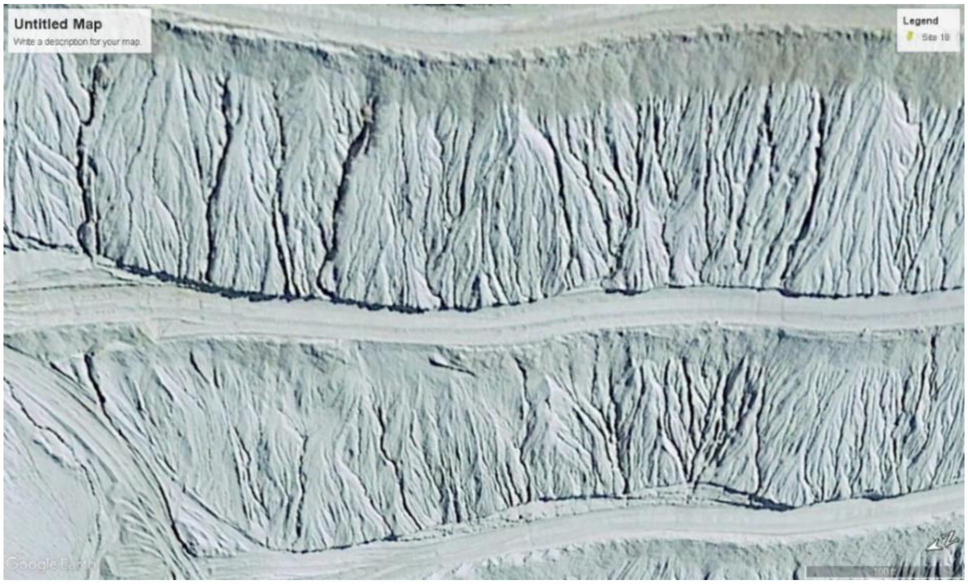


Figure 22: An image example captured using Google Earth Pro located in Arizona, USA.

4.3 Data Preparation

The final total data were 38 images to be labeled. Image labeling or annotating is the next step in data preparation. This process is recognized as the most time-consuming process compared to trying out different machine learning algorithms on the model (Geron, 2017). The data labeling process is classified into three categories: utilizing existing labels, crowd-based, and weak labels (Roh et al., 2019). There is no prelabeled dataset available in the rill detection application nor extra labor or capital to label all of the rill features, thus manual weak labels were generated for the time being. Weak labels combat quality with the quantity of annotated images. However, extra time was still allocated in this study to properly label the images since those have limited availability for TSFs with rill features.

Precise labeling is highly encouraged for this research as previously explained. Matlab has a labeling app ready for use, but it took a lot of time to label a single image properly. As seen in Figure 22, the number of rills to be labeled in a single image looks overwhelming. The right way of labeling features for machine learning is by marking the pixels of the mentioned features in detail. All visible rills should be marked and those must be within its boundaries. An image manipulator software called GIMP was a feasible option and user friendly (Chastain & Pfaffman, 2006). The *Fuzzy Select* (Magic Wand) is the built-in tool to select areas of an image based on color similarity. A trick with this tool is to pick the right starting point. Therefore, changing the image to grayscale would help to streamline the color similarity algorithm better. These selected regions were then marked with bright red colors to be easily separated (see Figure 23). Extra attention should be given not to annotate tire marks, shaded areas, or anything on the ground level. The rill features in concern are going down the dam walls. Images were finally extracted out after adjusting the resolution to 4800×2880 for easy convention.

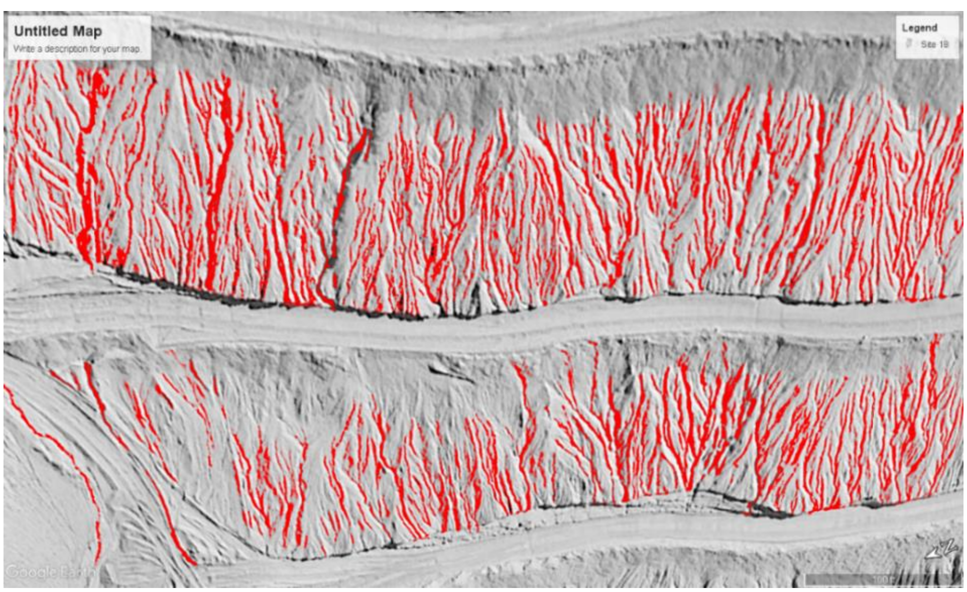


Figure 23: Annotated image showing red lines as the rills.

Afterward, all annotated images are translated to mask images. Matlab was employed for this step since it offered the most straightforward process. A suitable feature in Matlab was the ‘Color Thresholder’. It provided a user-friendly interface and an exportable setting in a form of coded script. There are four color spaces available to choose for separation of background and foreground namely RGB, HSV, YCbCr, and L*a*b*. After trying all the options, the HSV color space came out as the best way of separating the red pixels from the rest of the image. This color space allowed setting the threshold for three channels such as H (hue), S (saturation), and V (value/lightness). Table 7 below shows the settings of each channel that resulted in a better annotation translation into a Black & White mask. The Matlab script resulted from this setting can be easily applied to all other images in the data set. The scripts are provided in Appendix 1 of this thesis.

Table 7: Threshold settings for image mask creation.

Channel	Min Setting	Max Setting
Hue (H)	0.980	0.026
Saturation (S)	0.396	1.000
Value/Lightness (V)	0.396	1.000

Figure 24 presents how the mask image looks like after the thresholding stage. Another important item for machine learning images is to make sure that both the original image and the resulting mask are of the same resolution. Therefore, the resulted masks were also 4800×2880.

The later section will dive into how the model is trained and the final model after testing and tuning different hyperparameters setting.

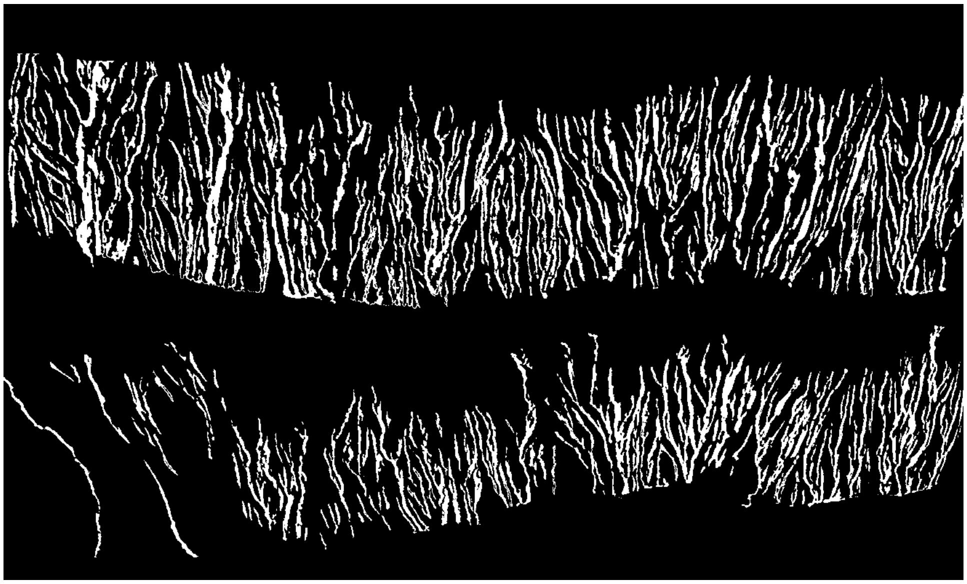


Figure 24: Masked label created with Matlab from the annotated image.

4.4 Model training and Fine-tuning

The next step in the development of a machine learning model is to train it using the images collected in a dataset. Model training in Matlab was the easiest initial option where it has a built-in function. A line of code can represent a whole architecture of UNet layers. It reduced the overall coding time. However, it was slightly problematic when an error was found since most functions cannot be sliced open and examined directly.

The images were first loaded into the workspace by storing them in *Datastore*. This step was the best way of storing a collection of image files by directing it to the corresponding folder location in the computer without separately loading them into Matlab workspace. Original images were stored with *imageDatastore* function, and the mask images were stored with *pixelLabelDatastore* function. An *imageDatastore* is commonly used for many applications not related to semantic segmentation necessarily; however, *pixelLabelDatastore* uses the *read* function in Matlab but more specific to reading pixel label data for semantic segmentation. It combined the mask image, classes given, and ID of each class. The class for each pixel is either “rill” or “background.” Mask example is shown in Figure 24: Masked label created with Matlab from the annotated image. is using black as background and white as rills; thus, the pixel value is either 0 or 225 respectively. A side note, the original image was transformed into grayscale which uses an 8-bit pixel range from 0 to 255, so the masks generated were using the same range. Both datastores were then combined in one datastore that connects original images to the corresponding mask.

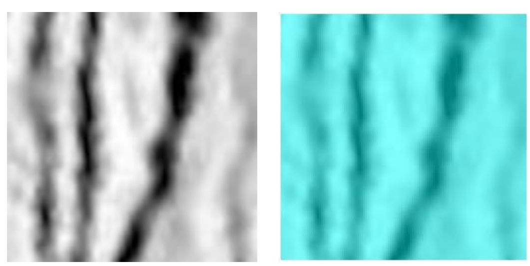
UNet network architecture creation in Matlab was straightforward. The function used was *unetLayers*, and the parameters feed were the sizes of images and the number of classes assigned to mask. Image size was 4800×2886 and there were two classes (rill and background). This input will let the network know that images stored in datastores are of such sizes and pixels that can be labeled as either of the two classes. Hyperparameters required to be assigned in Matlab are the learning rate (lr) and the loss function selected to train the model. Table 8 represents the selected values for the initial model training (The descriptions for these hyperparameters were presented in Chapter 3.) The *sgdm* loss function is a training algorithm that accelerates training by picking training instances randomly and computes the gradient on that particular instance before moving on to the next point (Geron, 2017).

Table 8: Hyperparameters assigned to the first Matlab model.

Hyperparameter	Value
Learning rate (lr)	1e-3
Loss function	sgdm – Stochastic Gradient Descent with Momentum

An issue was discovered after running the first code trial. The large images were using all available processing memory, thus disabling further data processing. This issue is commonly encountered due to the reverse pass of backpropagation requirement (Geron, 2017). The common remedy in this situation is through image partitioning where large images tiled into small image patches. The common practice for image tiling is by following the 2^n patch size rule. Images were initially tiled to 2^6 (64×64) patch size images, but it was too small for the team to recognize whether it was showing rills or not. Therefore, the next size up was selected (i.e., 2^7) resulting in a total of 13,943 image tiles.

The first trial was not showing the best results. Figure 25 is a side-by-side comparison of the same tiled image used in the model training. It took more than 88 hours to train the model and it could not detect any of the rill pixels. In other words, the model predicted the whole image areas belonging to the 'background class.'



(a) (b)

Figure 25: Initial model training result from Matlab. (a) tiled train image (b) the same image with the prediction from the trained model overlaid.

The most effective way of debugging the codes was to adjust the hyperparameters assigned to the model training process. Therefore, the model training was relocated to Python for simplicity. Python 3.6.10 was employed during this process. The model training with Python was similar to Matlab, but it required creating the UNet architecture and loss function manually. Figure 26 shows the UNet layers constructed to fit into this research. It has the same 27 filters as the original UNet architecture. The only difference between this architecture and the example shown in the previous chapter (Figure 20) would be the size of the input image and the addition of padding to keep image sizes constant within each step. The UNet architecture included *Batch Normalization* as well to improve accuracy and balance the effort of dropout regularization to avoid overfitting. The final detailed UNet architecture is available in Appendix 1. Packages used in Python were also different from Matlab where Python utilized packages such as *Keras* and *TensorFlow*. The Keras library was recommended for Python beginners since it is easy to learn and use (Moolayil, 2019). Also, Keras is one of many high-level APIs (Application Programming Interfaces) independently built on TensorFlow (Geron, 2017).

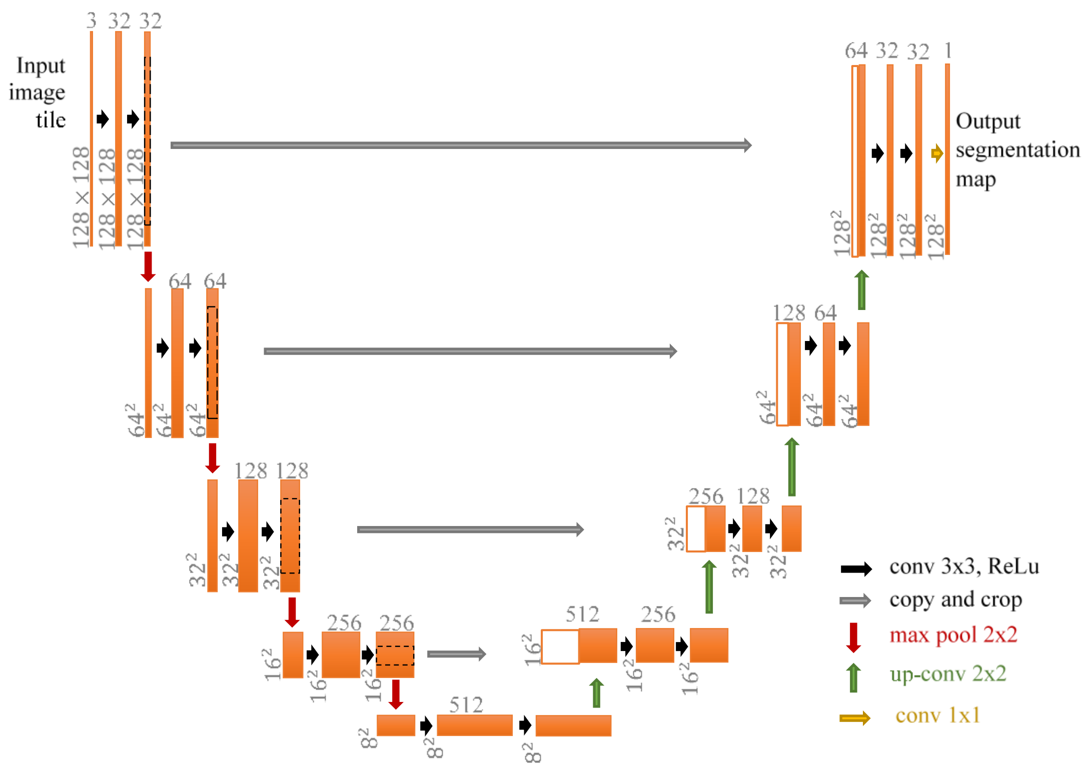


Figure 26: The constructed UNet architecture employed for model training.

The same training data were used for this model with a slightly different setup. The data were manually divided into training and validation sets. A common rule of thumb in machine learning is 80/20 where 80% of data are given to train the model and 20% of data for model validation. The training and validation tiles were then divided into 11,155 and 2,788 images (detailed in Table 9). Each dataset consists of a pair of input and mask folder containing the same amount of data. Input signifies the original image patches, and the mask contains the Black & White patches. Furthermore, data generator functions were applied including rescaling, horizontal flip, and vertical flip with a seed value of 100. Assigning seed value is important to make sure that the data reading order stays the same. This would let the model trained and validated with different orientations of the feed images while keeping the randomness within the selected seed value (Geron, 2017).

Table 9: Number of training and validation data.

Item	Amount
Training	11,155
Validation	2,788
Total	13,943

The UNet architecture developed to train the model was similar to the common network design. It had the same nine steps of convolution and non-linear activation function combinations (see Figure 26). The given example in subchapter 3.3.1 (Figure 20) had larger input images compared to the ones in this study. Furthermore, the employed optimization function was the weighted cross entropy using Adam optimizer. This loss function is commonly used for a dataset where the background data is largely abundant than the desired class (Asokan, 2019). Furthermore, Adam optimizer is a type of adaptive algorithm regarded as more robust since it includes bias corrections during model training

(Goodfellow et al., 2016). Model training was done in a server with specifications of 64 GPUs and 26 MB of RAM.

Almost all model training in machine learning requires fine-tuning. In this new model, several hyperparameters can be adjusted such as loss rate, weight factor, dropout rate (regularization method), batch size, and image patch size. The main objective of model training is to reduce the loss value (calculated with the selected loss function, i.e., weighted cross entropy) as more input data are given; therefore, the expected trend is to decline as iteration continues. The loss value implies how well or poorly the model behaves after each epoch (iteration).

Figure 27 displays the losses on the training and validation data during the model training. It shows that the training loss gradually decreases toward zero and similar trend is followed by the validation curve. The validation loss was initially very high then it decreases and follows a similar trend after 20 epochs as the model generalizes. The performance of this metric served as the indicator that the model could be performing well. If the validation curve does not follow the trend of the training curve asymptotic toward zero, then the model is overfitting. Overfitting means the model is simply memorizing the training data by heart, thus unable to predict new data properly (Goodfellow et al., 2016). On the contrary, the model is considered underfitting when the training loss is not asymptotic toward zero meaning it is too simple to learn the complexity of the current data structure (Geron, 2017).

The values of final hyperparameters for this last model are listed in Table 10. Curves shown in Figure 27 were obtained after adjusting the values to what’s presented in Table 10. It means that the best result was obtained by adapting the model to the model to the problem with the rate of 0.0001, assign 70% importance for the model to correctly label rill pixels, feeding 128 images at a time until all images were passed in each epoch, randomly dropping 3 out of 10 inputs within the hidden layers from each updated cycle, and perform 100 complete passes through the training data.

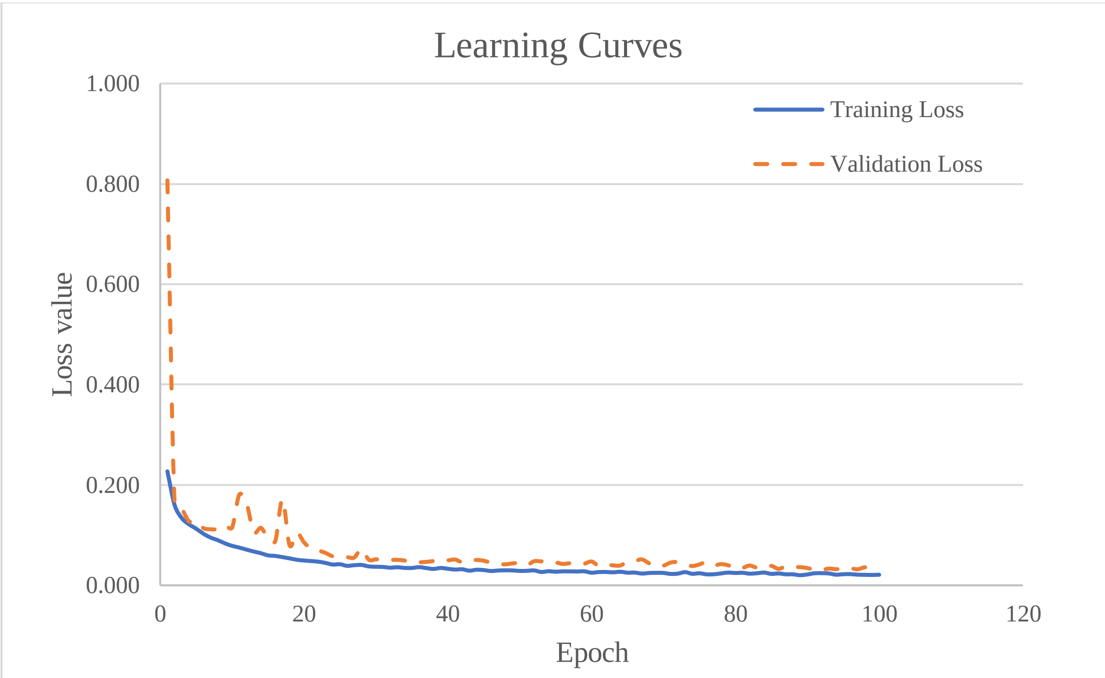


Figure 27: The learning curves during training from the training and validation data.

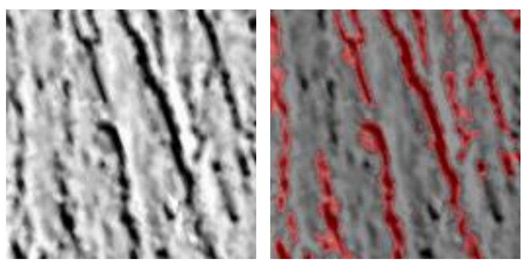
Table 10: Hyperparameters values for training in the Python model.

Hyperparameters	Value
Learning rate (lr)	0.0001
Weight factor	0.7
Batch size	128
Dropout rate	0.3
Epochs	100

The next section will go through the evaluation of the final model and how it relates to rill detection.

4.5 Results and Analysis

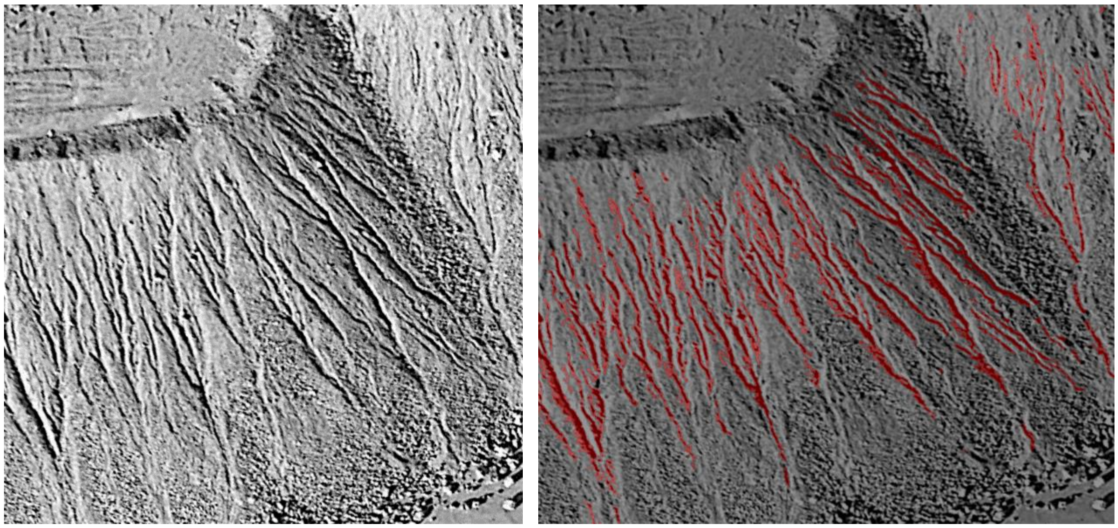
The final model training process took around 25 hours in total. It ran through all training and validation images tuned with hyperparameters listed in Table 10: Hyperparameters values for training in the Python model. It was first tested qualitatively by overlaying the predicted mask with the original image. A common model evaluation would start by looking at the accuracy, precision, and recall values to determine how good the model performs. However, rill detection with machine learning model is a new approach in the mining industry, so the evaluation process is the other way around compared to the usual machine learning application.



(a) (b)

Figure 28: The preliminary result of the model on the small image tile. (a) the original tiled image (b) the predicted mask showing rills in red highlights overlaid on (a).

Displayed in Figure 28, the model was effective when tested on a tile (128×128 size) from the training set. This initial test result showed that the model was able to predict rill pixels on the same image pacts used in the training data. There are some areas where the model predicted some areas as rills and some as not when it should have been. Another test was done on a larger patch (1024×1024 size) sectioned from one of the original images. Figure 29 reveals that the model responds qualitative well on different input sizes. This second test covered more areas with multiple types of rill complexity. The model was effective in predicting rills when they are visibly contrasted and when they are not as seen in the right area of Figure 29.



(a) (b)

Figure 29: The preliminary result of the model in a region in Image 8. (a) The selected region in the original image (b) the same region with predicted rill mask overlay.

The accepted model testing procedure of a machine learning model is by feeding new input data. This test will show the model's capability of detecting the rill features on something it has never seen before (i.e. how general is the resulting model). Six randomly selected regions from the original images and two new images were set aside for this task. Each patch is 400×400 in size showing various amounts and shapes of rill exposure. The resulting prediction masks quantitatively proved effective rills detection (Figure 30). Model's predicted areas are still represented by red highlights and all five test images are qualitatively labeled correctly.

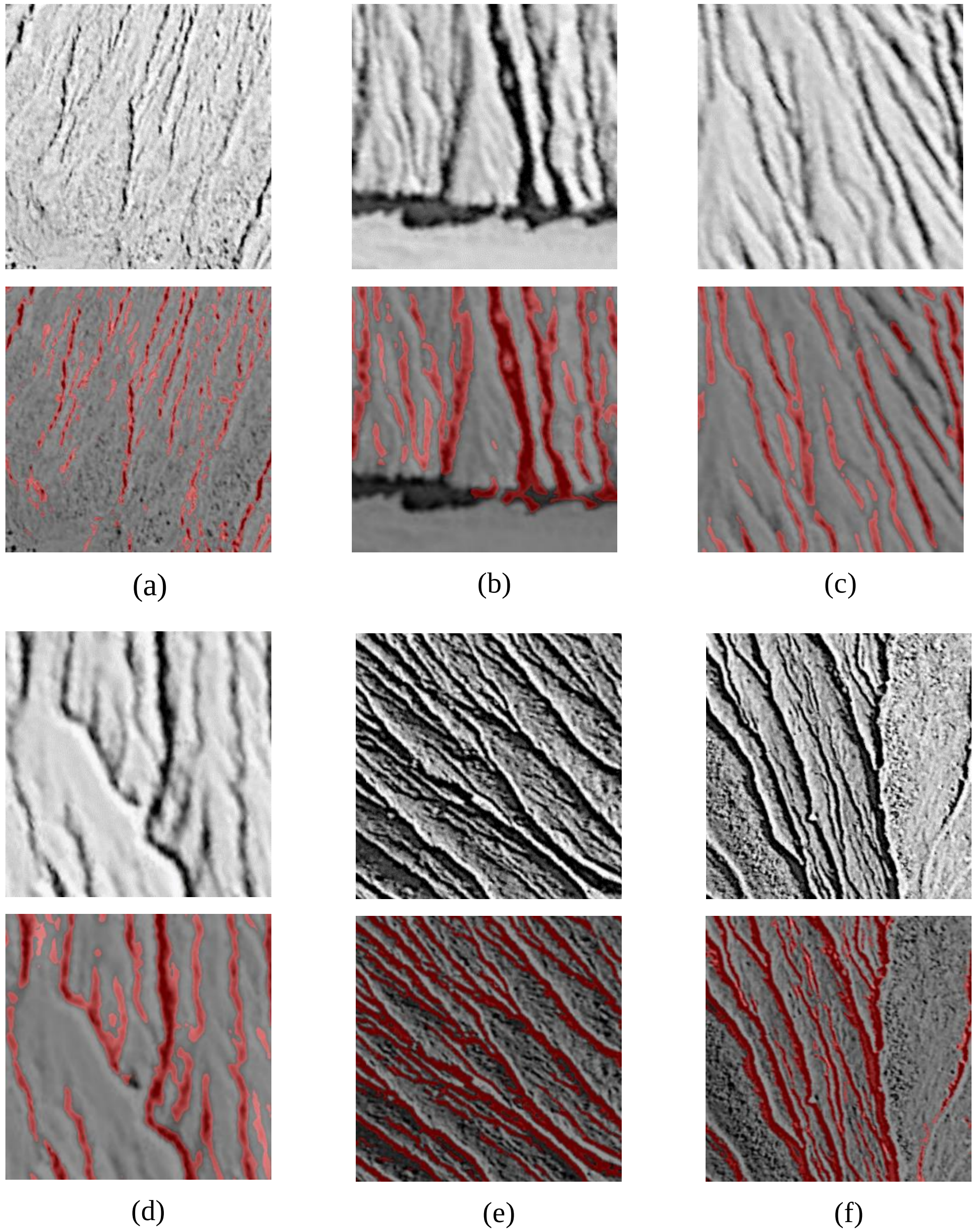


Figure 30: Comparison between the input images and the predicted result overlays for test data.

Areas selected were meant to test the model's capability of predicting different rill situation. Figure 30(a) tested and presented if it can predict when there is a lack of contrast between the rills and the wall. The model predicted all visible rills, but there are still some background pixels predicted as rills. Figure 30 (b) and (d) tested images with different rill width and more curvatures. There are some shadow areas within (b) where the model thinks that these areas are a part of the rill class. This means that more images with shadows should be given in the training set to let the model learn more instances with shadowy areas. Figure 30(c) assessed rills with similar widths. The model predicted these rills but there are areas where it did not. It could translate that more detailed labeling is required to refine further model creation. The last two patches Figure 30(e) and (f) displayed images with defined contrast between the rills and background. The model could easily detect these rills, so it is effective for this type of data. It could give the idea that further model should apply data augmentation with different levels of contrast and brightness.

Next, a qualitative test was performed. This test considered how many pixels were correctly labeled. The model is evaluated by calculating precision, recall, and F1-score. Precision (Eq. 3) measures the positive predictive value, recall (Eq. 4) measures the sensitivity of the predicted label, and F1-score (Eq. 5) represents the accuracy of the test based on precision and recall values (Winkelmaier et al., 2020). The parameters needed to calculate these metrics were acquired through the confusion matrix. Figure 31 illustrates how the matrix is constructed. The element with high significance is a True Positive (TP) value. TP signifies the correctly predicted pixels labeled as the feature. False Positive (FP) shows the number of background pixels labeled as feature pixels. False Negative (FN) is the invert of FP. True Negative (TN) is the amount of correctly labeled pixels as background pixels (Geron, 2017).

$$\text{Precision}=\frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \tag{3}$$

$$\text{Recall}=\frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \tag{4}$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

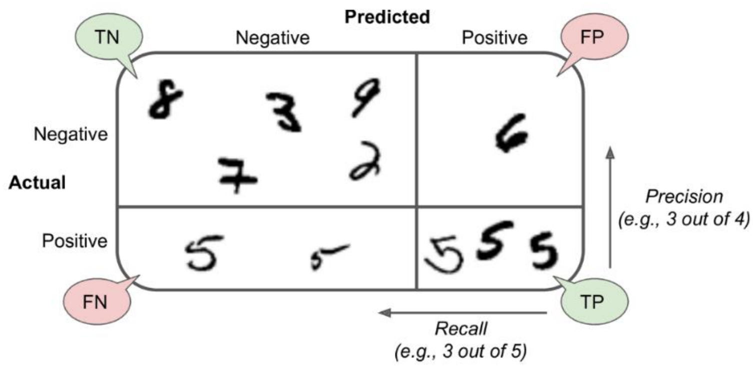


Figure 31: Illustration of a confusion matrix (Geron, 2017)

Table 11: Cumulative confusion matrix elements of the test data.

Matrix Element	Value
True Positive (TP)	185,908
False Positive (FP)	337,377
True Negative (TN)	664,520
False Negative (FN)	72,195

Elements of the confusion matrix from all test data are detailed in Table 11. These values were then utilized to calculate the evaluation metrics where results are shown in Table 12. The precision value means the model will correctly label “rill” within the input image 83.3%. Precision is a more suitable metric to evaluate a machine learning model because it only considers the correctly labeled pixels, which what the interest is, while accuracy looks at the ratio of correctly labeled pixels to the overall image pixels (Goodfellow et al., 2016). Moreover, it correctly predicted 72.0% of the overall rill pixels. Lastly, another term for F1-score is the harmonic mean or weighted average of recall and precision (Geron, 2017). This score is the preferred way to evaluate a neural network model with a large class imbalance (Pedregosa et al., 2013). Therefore, the value means that the trained model is 77.2% accurate in predicting the rill pixels.

Table 12: The evaluation metrics used to quantitatively measure the model's performance.

Evaluation Metrics	Result (%)
Precision	83.3
Recall	72.0
F1-score	77.2

The novelty of this study means that there is no threshold available to classify the "goodness" of model created. The rule of thumb in computer science application is that model is accepted within standard if values of evaluation metrics are more than 70%.

In conclusion, developing a machine learning model is a challenging process yet will produce an effective way to aid different activities. This study had a challenging data acquisition process, but it allowed the researcher to explore another acquisition method. Images captured through the Google Earth Pro platform showed the potential to serve as suitable input data to detect rill erosion on tailings impoundments. The UNet architecture provided favorable results in assisting rills detection with the application of the weighted cross entropy loss algorithm.

CHAPTER 5 : CONCLUSIONS AND RECOMMENDATIONS

Tailings dams have always been sources of liabilities for mine sites. It does not create profit, yet it requires extra attention to prevent dam failure. Too many failures associated with any kind of dams result in financial loss, environmental damage, and loss of lives. Most TSF guides suggest creating a monitoring program. Visual inspection is a highly recommended aspect of surveillance because it is perceived as the best way to identify issues. This study was built on the need for an effective way to aid visual identification of monitored parameters in TSFs. In addition, failures were tied with the constant change of managerial. The research looked at the possibility to apply machine learning to automate the detection procedure by processing images taken with UAVs (i.e., drones). Therefore, automation coupled with tailings surveillance system would address both issues at the same time.

Several studies were done in the past looking at utilizing UAV for TSF monitoring and monitored erosion on tailings impoundment as shown in Table 6. Rauhala et al. (2017) were the most recent in terms of UAV use and it found precise results in movement and displacement. They were able to link the changes to sheet erosion which was detectable due to the time range between each data acquisition. The machine learning model presented in this thesis showed that it is feasible to automate the detection and monitoring of rills erosion which does not require a long waiting period between data acquisition sessions. Slingerland et al. (2018) employed both LiDAR and aerial images in the identification and quantification of erosion on a sand tailings dam. It proved a similar requirement that expert opinion is needed to correctly identify the signs of erosion. However, this thesis took that concept and utilize automation in the detection by looking at Google Earth images. The automation process suggested in this study would reduce the engineer's time spent significantly in going through images one by one and determine locations of erosion signs.

The trained model in this study showed promising performance. It was evaluated qualitatively and quantitatively to determine the feasibility of the proposed method. Qualitative evaluation proceeded initially due to the novel nature of the study and objectivity of the feature. Quantitively measured, the value of precision, recall, and F1-score were 83.2%, 72.0%, and 77.2%, respectively. These performance metrics were accomplished by fine-tuning multiple hyperparameters such as batch size, image patch size, learning rate, weight factor, and dropout rate. The final model also attests that an image segmentation problem can be solved effectively through the UNet architecture with loss value calculated through the weighted cross entropy function.

Several recommendations surfaced after the conclusion of this research. The followings are some that can potentially increase the current model's performance.

- Theoretically, when more images are fed into the training and validation datasets, the possibility to further generalize the model expanded. Therefore, the first recommendation is to increase the number of training data. It might lead to reducing the values of performance metrics; thus requiring another fine-tuning of the hyperparameters or changing the selected loss function.
- Finer rills labeling can increase the qualitative performance of the model since detailed, annotated input will lead to detailed and precise predictions. Thus, more time should be allocated to data preparation.

- Similar to the previous point, the third recommendation is to expand the input data with more augmentation settings such as different brightness, contrast, rotation, and shear transformation.
- Winkelmaier et al., (2020) utilized a digital elevation model (DEM) image data in building their model. Thus, better results might be achieved by replacing the image data with the DEM files collected with drones to capture precise elevation differences. UAV acquisition method is recommended for it has a higher resolution than satellite-acquired DEM.
- The study done by Winkelmaier et al. (2020) proved the capability of ENet architecture in predicting tension cracks instead of rills. Therefore, the next recommendation is to try training the model with ENet architecture and reevaluate if it advances the performance.

Lastly, there lies a possibility to develop a new evaluation index based on the results. The index serves to quantify the erosion severity and as a result, the risk of instability, and to recommend preventive measures on different index levels. Listed below are proposed methods to create the index:

- The first proposed index creation is based on the rill length. A preliminary algorithm for implementing such index requires post-processing rill pixels to remove the gaps using morphological operations. Next, the connected components of the image should be extracted. Finally computing the image skeleton can produce a line image. To calculate the length various approaches may be used e.g. counting the total number of pixels or calculating the Euclidean distance between the line endpoints. The distance might be unreliable if generated from regular images since it is relative to the angle in which pictures were taken. Therefore, it might be more effective when coupled with DEM data. Gradient change is easily identifiable on this datatype, so it might improve the manual path assigning. Winkelmaier et al. (2020) used this method to segment benches and ramps in an open pit mine. Furthermore, utilizing morphological operations on the preprocessed image allow filtering features and categorize them based on the width for rill or gully.

- The previous method can add to this next recommendation. Another index can be generated through a heat map. This process can utilize a square box (e.g. $1m^2$) as a filter and slide it across the whole image. It can apply an algorithm to calculate the number of lines detected on each point of the box. The output is then translated to a heat map representing the number of rills per $1m^2$.
- When the rill lines from the previous point are combined and divided over the total area, the result can be considered as the rill density. An index generated from the density is on the next level after the current soil erosion index. The existing erosion index is based on volume loss which requires a long observation period or finding archived data. An index based on the rill density will have the potential to provide an insight immediately. The addition of rill width could also expand the forecast of gully development.

In conclusion, the index categorization will still require expert opinion to compare the rills captured in the image and the field condition. Also, this thesis serves as a methodology and proof of concept to apply deep learning to TSF monitoring program. However, images utilized were not from UAV, so the author recommends the work to be repeated with high-quality drone images. This research itself is a part of five years project, so future studies will cover the rest of visual

REFERENCES

ANCOLD. (2019). *Guidelines on tailings dams: planning, design, construction, operation and closure*. Tasmania, Australia.

Armstrong, M., Petter, R., & Petter, C. (2019). Why have so many tailings dams failed in recent years? *Resources Policy*, *63*, 101412. https://doi.org/10.1016/j.resourpol.2019.101412

Asokan, R. (2019, January 3). Neural Networks Intuitions: 1.Balanced Cross Entropy. Retrieved July 7, 2020, from https://towardsdatascience.com/neural-networks-intuitions-1-balanced-cross-entropy-331995cd5033

Bashir, S., Javed, A., Bibi, I., & Ahmad, N. (2017). *Soil and Water Conservation*.

Battulwar, R., Winkelmaier, G., Valencia, J., Naghadehi, M. Z., Peik, B., Abbasi, B., … Sattarvand, J. (2020). A Practical Methodology for Generating High-Resolution 3D Models of Open-Pit Slopes Using UAVs: Flight Path Planning and Optimization. *Remote Sensing*, *12*(14), 2283. https://doi.org/10.3390/rs12142283

Brownlee, J. (2019, July 5). A Gentle Introduction to Computer Vision. Retrieved July 23, 2020, from Machine Learning Mastery website: https://machinelearningmastery.com/what-is-computer-vision/

CDA. (2007). *CDA Dam Safety Guidelines Technical Bulletins Set*. Retrieved from Canadian Dam Association website: https://www.deslibris.ca/ID/480200#details=1

CDA. (2013). Dam Safety Guidelines 2007 (2013 Edition). In *Canadian Dam Association* (2013th ed.). Retrieved from https://issuu.com/canadiandamassociation/docs/cda_dam_safety_guidelines_2013_edit

Chastain, S., & Pfaffman, J. (2006). GIMP: GNU Image Manipulation Program. *Learning & Leading with Technology*, Vol. 33, pp. 54–55. Retrieved from https://www.gimp.org/

Clarkson, L., & Williams, D. (2019). Critical review of tailings dam monitoring best practice.

International Journal of Mining, Reclamation and Environment, *34*(2), 119–148. https://doi.org/10.1080/17480930.2019.1625172

Davies, M. P., & Rice, S. (2001). An alternative to conventional tailing management – “ dry stack ” filtered tailings. *Proceeding of Tailings and Mine Waste*, 411–420. https://doi.org/10.1016/j.oceaneng.2012.05.012

Dixon-Hardy, D. W., & Engels, J. M. (2007). Guidelines and Recommendations for the Safe Operation of Tailings Management Facilities. *Environmental Engineering Science*, *24*(5), 625–637. https://doi.org/10.1089/ees.2006.0133

Fell, R., MacGregor, P., & Stapledon, D. (1992). *Geotechnical Engineering of Embankment Dams*. Rotterdam.

FEMA. (2004). *Federal Guidelines for Dam Safety*. Retrieved from Federal Emergency Management Agency website: https://www.fema.gov/media-library/assets/documents/2639

Ferreira, E., Brito, M., Balaniuk, R., Alvim, M. S., & Santos, J. A. Dos. (2020). *BrazilDAM: A Benchmark dataset for Tailings Dam Detection*. Retrieved from http://www.patreo.dcc.ufmg.br/brazildam-dataset/

Frith, R., & Colwell, M. (2011). 8.5.3.3 Remote Sensing of Ground Deformation. In P. Darling (Ed.), *SME Mining Engineering Handbook (3rd Edition)* (pp. 564–566). Society for Mining, Metallurgy, and Exploration (SME).

Gama, F. F., Paradella, W. R., Mura, J. C., & de Oliveira, C. G. (2019). Advanced DINSAR analysis on dam stability monitoring: A case study in the Germano mining complex (Mariana, Brazil) with SBAS and PSI techniques. *Remote Sensing Applications: Society and Environment*, *16*, 100267. https://doi.org/10.1016/j.rsase.2019.100267

Geron, A. (2017). *Hands-On Machine Learning with Scikit-Learn* (N. Tache, Ed.). Sebastopol: O’Reilly Media Inc.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.

Hu, J., & Liu, X. (2011). Design and implementation of tailings dam security monitoring system. *Procedia Engineering*, *26*, 1914–1921. https://doi.org/10.1016/j.proeng.2011.11.2384

Hyder, Z., Siau, K., & Nah, F. (2019). Artificial intelligence, machine learning, and autonomous technologies in mining industry. *Journal of Database Management*, *30*(2), 67–79. https://doi.org/10.4018/JDM.2019040104

ICME/UNEP. (1998). *Case studies on Tailings Management*. Retrieved from http://www.icme.comhttp/fwww.unepie.org

ICOLD. (1996a). *A Guide To Tailings Dams and Impoundments - Design, Construction, Use, and Rehabilitiation* (106th ed.). Paris: International Commission on Large Dams.

ICOLD. (1996b). *Tailings Dams and Environment Review and Recommendations* (103rd ed.). Paris: International Commission on Large Dams.

ICOLD. (2001). Tailings Dams Risk of Dangerous Occurrences. In *International Commission on Large Dams* (121st ed.). Paris: International Commission on Large Dams.

ICOLD. (2018). *Dam Surveillance Guide (Gide de la Surveillance)* (158th ed.). Paris: CRS Press/Balkema, Taylor & Francis Group.

ICOLD. (2019). Tailings Dam Design - Technology Update. In *International Commission on Large Dams* (181st ed.). Paris: International Commission on Large Dams.

Jarosz, A. (2011). 9.4.3.2 Topographic Surveys. In P. Darling (Ed.), *SME Mining Engineering Handbook (3rd Edition)* (p. 733). Retrieved from https://app.knovel.com/hotlink/khtml/id:kt008JZUO2/sme-mining-engineering/topographic-surveys

Jeong, Y., & Kim, K. (2019). A Case Study: Determination of the Optimal Tailings Beach Distance as a Guideline for Safe Water Management in an Upstream TSF. *Mining, Metallurgy & Exploration*. https://doi.org/10.1007/s42461-019-00121-8

Johnson, A., Preston, M., Burkhalter, C., Krieger, G., Balge, Z., Lutes, K. K., … Lutes, K. K.

(2016). New remote sensing systems for improved planning and management of mine tailings storage facilities. *Proceedings Tailings and Mine Waste 2016, Keystone, Colorado, USA*, 891–903. Retrieved from www.theirm.org

Kerr, T., & Ulrich, B. (2011). 8.10 Tailings Impoundments and Dams. In P. Darling (Ed.), *SME Mining Engineering Handbook (3rd Edition)* (3rd ed., pp. 645–665). Retrieved from https://app.knovel.com/hotlink/toc/id:kpSMEMEHE5/sme-mining-engineering/sme-mining-engineering

Kossoff, D., Dubbin, W. E., Alfredsson, M., Edwards, S. J., Macklin, M. G., & Hudson-Edwards, K. A. (2014, December 1). Mine tailings dams: Characteristics, failure, environmental impacts, and remediation. *Applied Geochemistry*, Vol. 51, pp. 229–245. https://doi.org/10.1016/j.apgeochem.2014.09.010

Lamba, H. (2019, February 17). Understanding Semantic Segmentation with UNET. Retrieved July 17, 2020, from Towards Data Science website: https://towardsdatascience.com/understanding-semantic-segmentation-with-unet-6be4f42d4b47

Lee, C., Kim, S.-M., & Choi, Y. (2019). Case Analysis for Introduction of Machine Learning Technology to the Mining Industry. *Tunnel and Underground Space*, *29*(1), 1–11. https://doi.org/10.7474/TUS.2019.29.1.001

Leonida, C. (2019, August). Technology to Tackle Tailings. Retrieved June 29, 2020, from Engineering and Mining Journal website: https://www.e-mj.com/features/technology-to-tackle-tailings/

Li, Q. M., Wang, Y. H., & Li, G. (2011). Tailings dam breach disaster on-line monitoring method and system realization. *Procedia Engineering*, *26*, 1674–1681. https://doi.org/10.1016/j.proeng.2011.11.2353

Lumbroso, D., McElroy, C., Goff, C., Collell, M. R., Petkovsek, G., & Wetton, M. (2019). The potential to reduce the risks posed by tailings dams using satellite-based information. *International Journal of Disaster Risk Reduction*, *38*, 101209. https://doi.org/10.1016/j.ijdrr.2019.101209

Lupo, J., & Scharnhorst. (2019). 58. Tailings Disposal and Management. In R. C. Dunne, S. K. Kawatra, & C. A. Young (Eds.), *SME Mineral Processing & Extractive Metallurgy Handbook* (pp. 1115–1131). Society for Mining, Metallurgy, and Exploration (SME).

Lyu, Z., Chai, J., Xu, Z., Qin, Y., & Cao, J. (2019). A Comprehensive Review on Reasons for Tailings Dam Failures Based on Case History. *Advances in Civil Engineering*, *2019*. https://doi.org/10.1155/2019/4159306

MAC. (2019a). *A Guide to the Management of Tailings Facilities* (3.1). Retrieved from https://mining.ca/documents/a-guide-to-the-management-of-tailings-facilities-version-3-1-2019/

MAC. (2019b). *Developing an operation, maintenance and surveillance manual for the post-closure management of tailings facilities* (Second). Retrieved from https://mining.ca/documents/oms-guide-second-edition-2019/

Mainali, G., Nordlund, E., Knutsson, S., & Thunehed, H. (2015). Tailings dams monitoring in Swedish mines using self-potential and electrical resistivity methods. *Electronic Journal of Geotechnical Engineering*, *20*(13), 5859–5875.

Mansouri, I. (2019, December 29). Computer Vision Part 6: Semantic Segmentation, classification on the pixel level. Retrieved July 17, 2020, from Analytics Vidhya website: https://medium.com/analytics-vidhya/computer-vision-part-6-semantic-segmentation-classification-on-the-pixel-level-ee9f5d59c1c8

MathWorks. (2018). Semantic Segmentation, 3 things you need to know. Retrieved July 24, 2020, from The MathWorks, Inc. website: https://www.mathworks.com/solutions/image-video-processing/semantic-segmentation.html

Moolayil, J. (2019). An Introduction to Deep Learning and Keras. In *Learn Keras for Deep Neural Networks* (pp. 1–16). https://doi.org/10.1007/978-1-4842-4240-7_1

OSHA. (2016). Recommended Practices for Safety and Health Programs. *A Safe Workplace Is Sound Business*, (October). Retrieved from www.osha.gov

Papert, S. (1966). *The summer vision project* (pp. 1–6). pp. 1–6. Retrieved from http://dspace.mit.edu/handle/1721.1/6125

Pathmind. (n.d.). A Beginner's Guide to Neural Networks and Deep Learning. Retrieved July 10, 2020, from Pathmind website: https://pathmind.com/wiki/neural-network

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., … Duchesnay, E. (2013). sklearn.metrics.f1_score. Retrieved July 26, 2020, from scikit-learn 0.23.1 documentation website: https://scikit-learn.org/stable/modules/generated/sklearn.metrics.f1_score.html

PenasquitoMine. (2020). *Penasquito_rgb*. Penasquito Mine, Mine Survey Team Documents.

Rauhala, A., Tuomela, A., Davids, C., & Rossi, P. M. (2017). UAV remote sensing surveillance of a mine tailings impoundment in Sub-Arctic conditions. *Remote Sensing*, *9*(12). https://doi.org/10.3390/rs9121318

Rico, M., Benito, G., Salgueiro, A. R., Díez-Herrero, A., & Pereira, H. G. (2008). Reported tailings dam failures. A review of the European incidents in the worldwide context. *Journal of Hazardous Materials*, *152*(2), 846–852. https://doi.org/10.1016/j.jhazmat.2007.07.050

Roh, Y., Heo, G., & Whang, S. E. (2019). A Survey on Data Collection for Machine Learning: A Big Data - AI Integration Perspective. *IEEE Transactions on Knowledge and Data Engineering*, 1–1. https://doi.org/10.1109/tkde.2019.2946162

Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. *International Conference on Medical Image Computing and Computer-Assisted Intervention*, 234–241. Retrieved from http://lmb.informatik.uni-freiburg.de/

Sattarvand, J., & Parvin, B. (2019). *Developing a New Tension Crack Analysis System to Increase the Safety of Open Pit Slopes*. Retrieved from https://nevada.app.box.com/s/b4d221e34p5pewpso5pgfh8fmix33lo2/file/539607203615

Schimmer, R. (2008). A remote sensing and GIS method for detecting land surface areas covered by copper mill tailings. *Pecora 17 - The Future of Land Imaging...Going Operational*, 1–13. Retrieved from http://clear.uconn.edu/publications/research/tech_papers/schimmer_pecora2008.pdf

Slingerland, N., Sommerville, A., O'Leary, D., & Beier, N. A. (2018). Identification and quantification of erosion on a sand tailings dam. *Geosystem Engineering*, 1–15. https://doi.org/10.1080/12269328.2018.1538823

Soleimany, A. (2019). *Deep Learning for Computer Vision MIT 6.S191*.

USACE. (2019). National Inventory of Dams - Interactive Maps & Charts. Retrieved March 9, 2020, from U.S. Army Corps of Engineers website: https://nid.sec.usace.army.mil/ords/f?p=105:113:8178099100327::NO:::

Vick, S. G. (1983). *Planning, Design, and Analysis of Tailings Dam* (1st ed.; T. W. Lambe & R. V. Whitman, Eds.). John Wiley & Sons, Inc.

Winkelmaier, G., Battulwar, R., Khoshdeli, M., Valencia, J., Sattarvand, J., & Parvin, B. (2020). Topographically Guided UAV for Identifying Tension Cracks using Image-based Analytics in Open-Pit Mines. *IEEE Transactions on Industrial Electronics*, 1–1. https://doi.org/10.1109/tie.2020.2992011

WISE. (2016). Chronology of major tailings dam failures. *WISE Uranium Project-Tailings Dam Safety*. Retrieved from http://www.wise-uranium.org/mdaf.html

Yang, L., Fan, Y., & Xu, N. (2019). Video instance segmentation. *Proceedings of the IEEE International Conference on Computer Vision*, *2019-Octob*, 5187–5196. https://doi.org/10.1109/ICCV.2019.00529

Zhang, J. (2019). UNet — Line by Line Explanation. Example UNet Implementation. Retrieved July 9, 2020, from Towards Data Science website: https://towardsdatascience.com/unet-line-by-line-explanation-9b191c76baf5

Zwissler, B., Oommen, T., Vitton, S., & Seagren, E. A. (2017). *Thermal Remote Sensing for Moisture Content Monitoring of Mine Tailings: Laboratory Study*. Retrieved from https://pubs.geoscienceworld.org/aeg/eeg/article-pdf/23/4/299/4046405/i1078-7275-23-4-299.pdf

APPENDIX 1 SOURCE CODES

- UNet Script in Matlab

```
%% Clean workspace
clc
clear all
close all

%% Load training data
dataSetDir = fullfile('C:\Users\fnasategay\Documents\TIRAS\Models');
imageDir = fullfile(dataSetDir, 'ori_tiles');
labelDir = fullfile(dataSetDir, 'lab_tiles');

%% Create Image Datastore for Images
imds = imageDatastore(imageDir);

%% Create a pixelLabelDatastore for the ground truth pixel labels
classNames = ["rill", "background"];
labelIDs = [225 0];
pxds = pixelLabelDatastore(labelDir, classNames, labelIDs);

%% Create the U-Net network
imageSize = [64 64];
numClasses = 2;
[lgraph, outputSize] = unetLayers(imageSize, numClasses);

%create datastore for the training network
ds = pixelLabelImageDatastore(imds, pxds);

%set training options
options = trainingOptions('sgdm','InitialLearnRate', 1e-3, 'MaxEpochs',
20, 'VerboseFrequency', 10);

%% Train the network
net = trainNetwork(ds, lgraph, options);
```

- Final UNet architecture in Python code

```
c1 = Conv2D(32, (3, 3), activation='relu',
kernel_initializer='he_normal', padding='same') (inputs)
c1 = BatchNormalization()(c1)
c1 = Dropout(0.3) (c1)
c1 = Conv2D(32, (3, 3), activation='relu',
kernel_initializer='he_normal', padding='same') (c1)
c1 = BatchNormalization()(c1)
p1 = MaxPooling2D((2, 2)) (c1)
```

```
c2 = Conv2D(64, (3, 3), activation='relu',
kernel_initializer='he_normal', padding='same') (p1)
c2 = BatchNormalization()(c2)
c2 = Dropout(0.3) (c2)
c2 = Conv2D(64, (3, 3), activation='relu',
kernel_initializer='he_normal', padding='same') (c2)
c2 = BatchNormalization()(c2)
p2 = MaxPooling2D((2, 2)) (c2)

c3 = Conv2D(128, (3, 3), activation='relu',
kernel_initializer='he_normal', padding='same') (p2)
c3 = BatchNormalization()(c3)
c3 = Dropout(0.3) (c3)
c3 = Conv2D(128, (3, 3), activation='relu',
kernel_initializer='he_normal', padding='same') (c3)
c3 = BatchNormalization()(c3)
p3 = MaxPooling2D((2, 2)) (c3)

c4 = Conv2D(256, (3, 3), activation='relu',
kernel_initializer='he_normal', padding='same') (p3)
c4 = BatchNormalization()(c4)
c4 = Dropout(0.3) (c4)
c4 = Conv2D(256, (3, 3), activation='relu',
kernel_initializer='he_normal', padding='same') (c4)
c4 = BatchNormalization()(c4)
p4 = MaxPooling2D(pool_size=(2, 2)) (c4)

c5 = Conv2D(512, (3, 3), activation='relu',
kernel_initializer='he_normal', padding='same') (p4)
c5 = BatchNormalization()(c5)
c5 = Dropout(0.3) (c5)
c5 = Conv2D(512, (3, 3), activation='relu',
kernel_initializer='he_normal', padding='same') (c5)
c5 = BatchNormalization()(c5)

u6 = Conv2DTranspose(128, (2, 2), strides=(2, 2), padding='same') (c5)
u6 = concatenate([u6, c4])
c6 = Conv2D(256, (3, 3), activation='relu',
kernel_initializer='he_normal', padding='same') (u6)
c6 = BatchNormalization()(c6)
c6 = Dropout(0.3) (c6)
c6 = Conv2D(256, (3, 3), activation='relu',
kernel_initializer='he_normal', padding='same') (c6)
c6 = BatchNormalization()(c6)

u7 = Conv2DTranspose(64, (2, 2), strides=(2, 2), padding='same') (c6)
u7 = concatenate([u7, c3])
c7 = Conv2D(128, (3, 3), activation='relu',
kernel_initializer='he_normal', padding='same') (u7)
c7 = BatchNormalization()(c7)
c7 = Dropout(0.3) (c7)
c7 = Conv2D(128, (3, 3), activation='relu',
kernel_initializer='he_normal', padding='same') (c7)
c7 = BatchNormalization()(c7)
```

```
u8 = Conv2DTranspose(32, (2, 2), strides=(2, 2), padding='same') (c7)
u8 = concatenate([u8, c2])
c8 = Conv2D(64, (3, 3), activation='relu',
kernel_initializer='he_normal', padding='same') (u8)
c8 = BatchNormalization()(c8)
c8 = Dropout(0.3) (c8)
c8 = Conv2D(64, (3, 3), activation='relu',
kernel_initializer='he_normal', padding='same') (c8)
c8 = BatchNormalization()(c8)

u9 = Conv2DTranspose(16, (2, 2), strides=(2, 2), padding='same') (c8)
u9 = concatenate([u9, c1], axis=3)
c9 = Conv2D(32, (3, 3), activation='relu',
kernel_initializer='he_normal', padding='same') (u9)
c9 = BatchNormalization()(c9)
c9 = Dropout(0.3) (c9)
c9 = Conv2D(32, (3, 3), activation='relu',
kernel_initializer='he_normal', padding='same') (c9)
c9 = BatchNormalization()(c9)

outputs = Conv2D(1, (1, 1), activation='sigmoid') (c9)
```

- Optimization function: Weighted Coss Entropy

```
def balanced_cross_entropy(beta):
   def convert_to_logits(y_pred):
        # see
        https://github.com/tensorflow/tensorflow/blob/r1.10/tensorflow/p
        ython/keras/backend.py#L3525
        y_pred = tf.clip_by_value(y_pred, tf.keras.backend.epsilon(), 1
        - tf.keras.backend.epsilon())
        return K.log(y_pred / (1 - y_pred))

   def loss(y_true, y_pred):
      y_pred = convert_to_logits(y_pred)
      pos_weight = beta / (1 - beta)
      loss = tf.nn.weighted_cross_entropy_with_logits(logits=y_pred,
      labels=y_true, pos_weight=pos_weight)

    # or reduce_sum and/or axis=-1
    return tf.reduce_mean(loss * (1 - beta))

  return loss
```