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Advances in the use of artificial intelligence for open pit reconciliation

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Abstract

Traditional means of undertaking reconciliation and performance measurements on open pit mines can be quite time-consuming and also labour-intensive. Furthermore, when comparing the actual or as-built pit against the underlying open pit design, the measurement of performance can be subjective based upon the practitioner's level of experience, nuances in the geometries being analysed and the time available to conduct the analysis.

With the advent and advancement of the use of artificial intelligence (AI) applied to mining problems, the key issues of time, availability, repeatability and accuracy of open pit reconciliation are being greatly improved. Specific tools and key performance indicators for pit reconciliation have been incorporated into an AI-based software platform, including crest loss, toe flare, available catch capacity, bench face angle, and volume of overbreak or underbreak etc., for fast and accurate pit reconciliation.

The measurement of key performance indicators such as these allow for the rapid and accurate assessment of drill and blast design performance. Reporting on compliance to design can quickly be fed back into the drill and blast process to optimise and improve outcomes.

Furthermore, the identification of potential non-conformance leading to hazardous areas in the pit (i.e. insufficient spill berm width coupled with rockfall hazard) can be easily communicated and incorporated into monthly geotechnical hazard maps for communication to work crews.

The process described is based upon the analysis of high-resolution photogrammetric models of the as-built pit environment. The AI-generated results are highly visual, can be displayed qualitatively and offer detailed quantitative reporting on conformance.

In order to validate the accuracy and sufficiency of the AI tools, significant time has been spent conducting manual validation on identical datasets, with very promising outcomes. This paper describes the application of AI, and the independent evaluation and verification of the results are presented herein. As with any use of AI, independent human verification is advised.

Keywords: *artificial intelligence, pit reconciliation, drone, crest loss, berm*

1 Introduction

Artificial intelligence (AI) can be described as the intelligence shown by computers as opposed to that which is shown by humans or animal intelligence. The word 'intelligence' indicates that there is an ability to reason, make generalisations or infer some kind of meaning from what is being sought or observed (Wikipedia 2023). The aim of AI could generally be described as one to replace human functions and processes with those conducted by machines or computers. It would seem that the intention has always been to develop an intelligence that can make decisions for us, and process very large sets of information and data, to essentially make human life easier.

The application of AI to problems in industry, particularly mining, is not new, but we are seeing broader application taking place and the speed at which it is being adopted appears to be quickening. The drivers for this could be linked to advances in computing power, a lack of human resourcing in the mining industry and the realisation that significant value can be gained by processing large bodies of data in very short periods of time: specifically, processes that we would traditionally perform as humans in our day-to-day roles on mine sites.

We could be considered as generally time-poor as practitioners. Due to our busy and time-poor lifestyles, we often find that important tasks on a mine site become performed less frequently, and the opportunity to learn or improve our practices comes second place to production.

This paper explores one such development of the application of AI-based analysis in the area of open pit reconciliation. The need for, and importance of, open pit reconciliation is explored, not just from a conformance-to-design perspective but for identification of deficiencies of the as-built physical environment, and how this impacts on safe operations within the open pit environment.

The capture and development of 3D photogrammetric models routinely occurs in mining and these models are rich in information, which is an important step in understanding our performance in the open pit environment. A quality model is fundamental to the reconciliation of open pits, and factors affecting the quality of developing such a model are discussed within this paper.

The fundamental process of AI and its development and application to resolving open pit reconciliation is described herein. There is long-recognised potential for AI to meaningfully contribute to the mining industry, and this paper aims to demonstrate one such application.

Importantly, verification and validation of the AI process has been conducted and assessed against the intended AI functions of open pit reconciliation. The keys measures of success in this instance are defined as: its accuracy, i.e. human-made reconciliation reports compare accurately to the AI-based reconciliation; and, perhaps most importantly, that this is undertaken in a significantly more time-efficient manner.

2 Open pit slope reconciliation

The majority of mine sites globally and throughout Australia gather a substantial level of data but only a small portion is fully utilised, and is often limited to basic tasks including volumetric reconciliations and wall sign-offs (crest and toe checks).

Converting raw data into useful insights has historically taken time and resources, with sites often not equipped to complete this on a regular basis. However, leveraging this data can enhance operational decisions. To complete this effectively there is a requirement on site to improve and streamline current workflows, ensuring the best use of limited resources while utilising the tools now available to the industry to complete tasks more effectively and to a higher level of accuracy.

The ability to capture aerial survey data via unmanned aerial vehicles (UAV) and incorporate a high-resolution photogrammetric model or LiDAR scan in comparison to the underlying slope design file ensures a robust and accurate model is developed which overcomes previous issues around a lack of adequate and reliable data. The ability to capture this data remotely allows for the removal of mine site personnel from hazardous regions of the pit.

As open pits are increasing in footprint dimensions and depth, ensuring compliance of the as-built pit to the engineered design is increasingly critical to the economics and safety of the operation (Dey et al. 2021).

The direct measure of crest loss or batter conformance allows for calibration of the existing bench stability analysis, enabling the data to be used in future risk modelling and slope optimisation; thus increasing confidence in the final design. The ability of an operation to achieve design should be assigned a weighting in subsequent design analysis and considered when reviewing wall cutbacks, optimisation programs or the development of new open pits.

Identification of sectors of pit walls where the available catch capacity is less than adequate, and development of correct control measures, can assist with improved rockfall risk management and operational practices on site. This process then allows for the identification and rectification of the failure mechanism that compromised the wall performance.

UAVs offer rapid data capture, and the correct use of AI can streamline workflows, allowing timely, data-driven decisions. This is vital for large pits with fast vertical growth. The ultimate goals are safety, compliance and value addition through reduced ore loss, hazard identification and ongoing optimisation. A systematic approach involving data collection, comparison with predictions and iterative design modifications ensures rational slope design.

3 Data capture and processing

The open pit as-built models that were used for pit reconciliations were derived from photogrammetric processing of aerial drone imagery. The models that can be produced from aerial surveys contain sufficient resolution for detailed visual and quantitative reporting of parameters such as crest loss, toe flare, overbreak and underbreak, and more, which would be difficult to accurately quantify using data obtained from other conventional survey methods.

With drones now commonly used in many open pit mining operations around the world, obtaining highly detailed and spatially accurate 3D models of pit excavations for geometric pit reconciliation has become more achievable. The latest drone technology and data processing software has made the capture, processing and handling of high-resolution data more efficient, enabling more frequent analysis and reporting to be performed.

3.1 Data capture methodology

The 3D models used for the evaluations described in this paper were generated from drone imagery that was captured with the parameters specified in Table 1.

Table 1 Aerial data capture parameters

Parameter	Description/methodology
Drone type	DJI Mavic 3 Enterprise real time kinematic (RTK) (small multirotor)
Image geolocation	The drones' RTK capability was used for applying accurate geolocation to each image, enabling a model of high spatial accuracy to be generated without ground control points applied in the processing. Surveyed check points were, however, used to verify the accuracy of the resulting model
Image orientations	Oblique imagery was captured with the drone following the contours of the pit, maintaining a constant 50 m separation from the pit wall
Ground sample distance	Average 1.3 cm per pixel
Image overlap	Nom. 80% forward, and 80% side overlap

Capturing nadir imagery of the pit will enable a 3D model of sufficient detail to be generated for accurate reconciliation reporting. This allows for simple flight planning using the default nadir mapping functionality that is inbuilt in most drone systems (such as the commonly used DJI Mavic 3 Enterprise illustrated in Figure 1). The capture of oblique imagery does, however, enable detail in the sub-vertical surfaces (batter faces) to be modelled. This is useful for visual inspection of those surfaces or for applying artificial intelligence to the mapping of structure in the rock mass (which is beyond the scope of this paper). Figure 2 illustrates the oblique image capture locations corresponding with the contours of a pit that was modelled. The pit in this example has dimensions of approximately 1,200 m length, 700 m width and 200 m depth, and involved the capture of 4,153 images over one day.

To enable accurate reconciliation of the pit models against the pit design, it is important that the model has high relative and absolute spatial accuracy. With the real time kinematic (RTK) capability that many drones being used on mine sites now have, this can be readily achieved with the use of no, or minimal, surveyed ground control points (GCPs). However, even with RTK drones, a small number of GCPs is recommended. For non-RTK drones, an increased number of GCPs will still generally enable adequate accuracy to be achieved, provided that the camera used is suitable for photogrammetric mapping.

Although not used in the evaluations discussed in this paper, 3D models suitable for accurate reconciliation reporting with AI have also been generated by RocketDNA using:

- Nadir imagery captured by drone at an average ground resolution approximately 5 cm per pixel.
- LiDAR and imagery data captured with fixed-wing manned aircraft at an image resolution of 10 cm per pixel and LiDAR point density of 20 points per square metre.

Figure 1 Capturing aerial imagery of an open pit with a DJI Mavic 3 Enterprise RTK drone for modelling and reconciliation in Strayos software

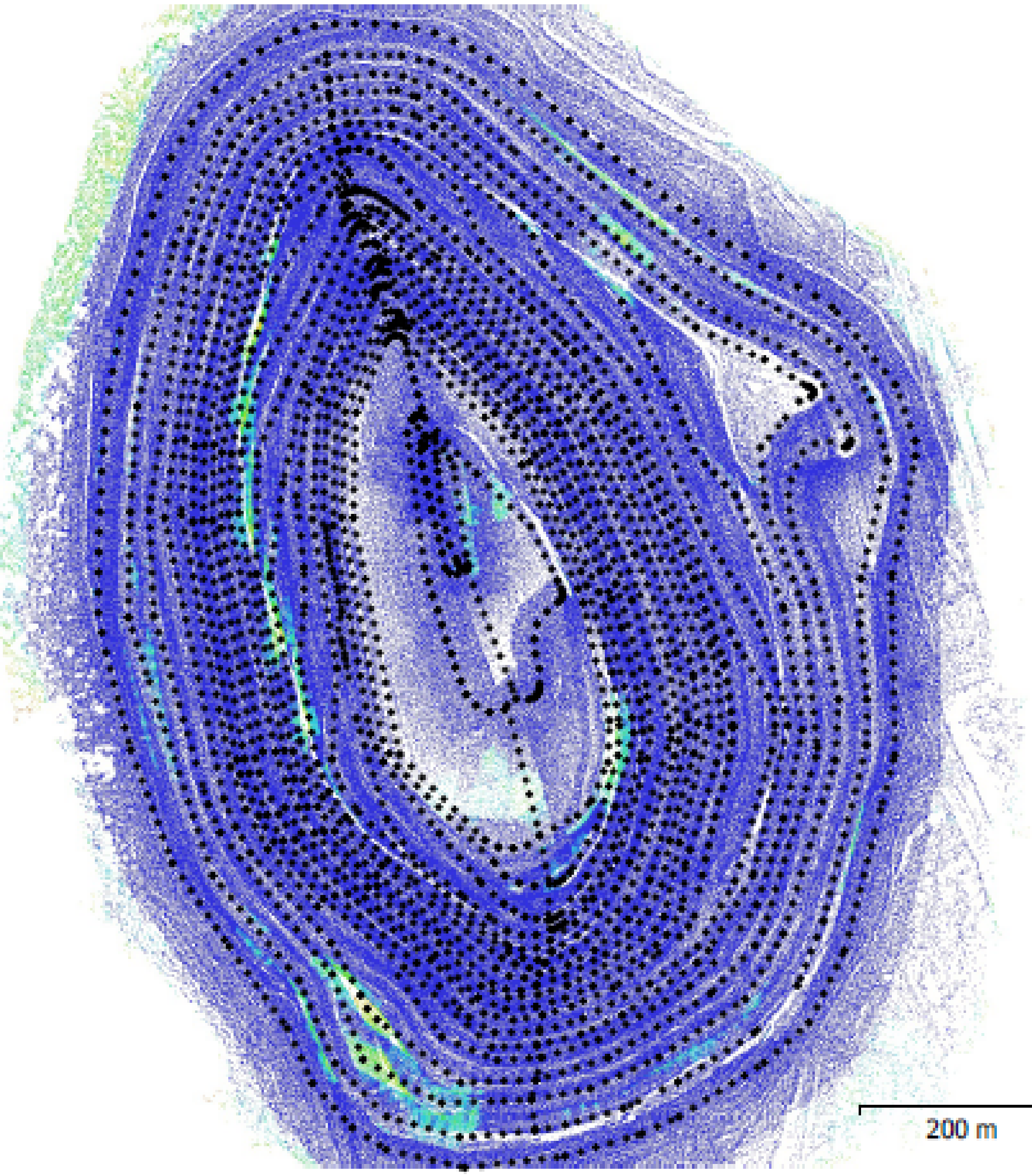


Figure 2 Oblique image capture locations (black dots) illustrating the capture of images parallel to the contours of the pit

3.2 Data processing

The models generated for the reconciliation reporting process were generated in Strayos software platform (Strayos Inc.).

Strayos includes a photogrammetry engine that enables the individual drone images to be uploaded directly into the cloud-based software, which then commences the processing to generate the full-resolution orthomosaic image and digital surface model (DSM) for 2D viewing, and the rendered 3D model (for 3D viewing, as illustrated in Figure 3). If surveyed GCPs are available, these are applied after the initial image upload and prior to the photogrammetry process.

Alternatively, the orthomosaic imagery and DSM can be generated in other photogrammetry software and then uploaded into Strayos for the reconciliation reporting. However, using Strayos to process the drone imagery and produce the model enables detail in the sub-vertical faces to be maintained in the case that oblique imagery has been captured.

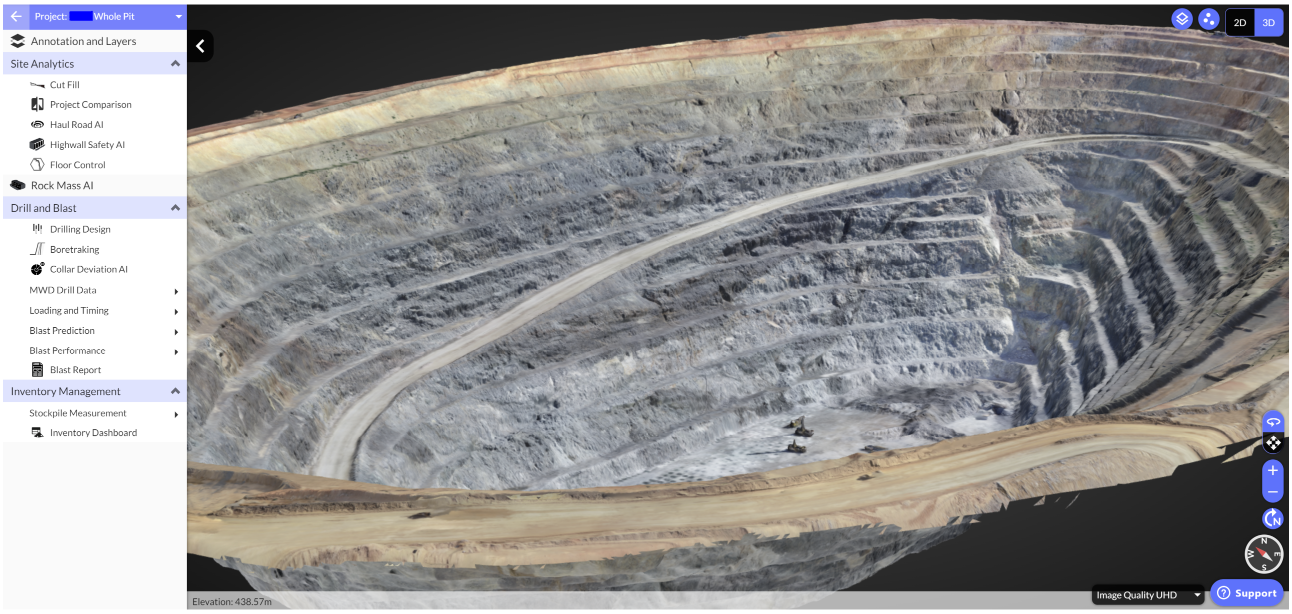


Figure 3 Rendered 3D model of an open pit generated in Strayos software from drone imagery

3.3 Automation of data capture and processing

With autonomous drone systems (also commonly referred to as 'drone-in-a-box' systems) now becoming more readily available, the automation of aerial data capture and processing for pit reconciliations is feasible.

Autonomous drone systems involve one or more drones located on site – each operating from a 'dock' – which can execute scheduled or on-demand flights, with oversight by a pilot in a remote operations centre. The captured data is then automatically uploaded to a cloud service once the drone completes the mission and returns to the dock. These systems will provide a cost-effective method of conducting more frequent capture of open pit as-built data, with the possibility of automated upload into software such as Strayos for generating the pit models required for reconciliation reporting.

4 Artificial model development and training

This section describes the prediction and filtering model developed for Highwall-AI.

4.1 Source data

The initial information used for detecting crest and toe lines consists of geolocated orthographic images and digital elevation model (DEM) files. A DEM provides the basic geometry required, while orthographic images help identify and remove trees and other objects that might interfere.

In simpler terms, we look at the slope angle of the land to find crest and toe lines. When the slope angle is high it indicates benches. The edges of these benches are either crest or toe lines.

However, sometimes the branches and crowns of trees on the DEM can create false benches. To address this, we employ a technique called semantic segmentation using a convolution neural network (CNN) with a UNet architecture.

4.2 Data preparation

The orthographic images were labelled in QGIS by manually marking them and then saving the results in corresponding GeoJSON files, as seen in Figure 4.

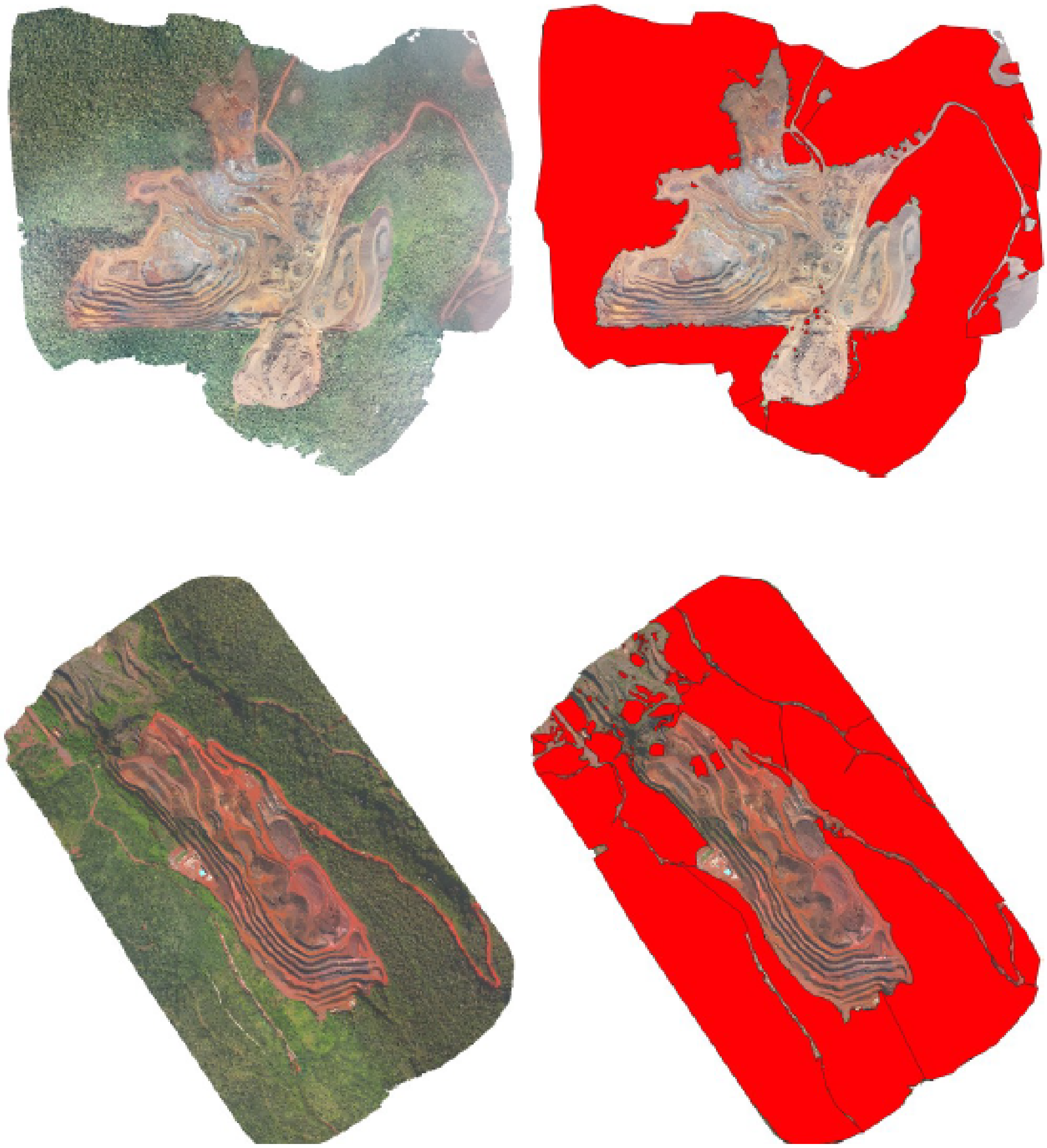


Figure 4 Orthographic images showing masking

This approach has advantages over traditional image labelling because it allows us to easily match different raster and vector data. The orthographic image, DSM and GeoJSON are all geolocated data, making it simple to align them.

During training, it is important to use data that corresponds to the same common ground sample distance (GSD). GSD is a control parameter that affects the accuracy of the model. The GSD value used during training should also be used in the inference pipeline to ensure consistent model performance.

Before training the model, a Python script crops the labelled orthographic images, rasterises the GeoJSON and creates a cosine field of the DSM. These cropped images will be used for training the model.

The cosine field represents the slope of the terrain at each pixel of the DEM. It helps the model distinguish between green benches, like those made of chromium oxide or nickel ore, and non-green trees.

The field of normals on the DEM is calculated as the normalised cross product of the derivatives in the X and Y directions. This field is used to determine the slope cosine.

$$\vec{N} = \| \frac{dZ}{dx} \times \frac{dZ}{dy} \| \tag{1}$$

where $\vec{N}$ is field normal on the DEM.

The cosine field is defined as a dot product between field of normals and vector OZ [0, 0, 1]

$$C = \vec{N} \odot [0,0,1] \tag{2}$$

where C is the cosine.

Training the model with a GSD value of 0.5 metres per pixel and a cropping size of 256 pixels (see Figure 5), was found to achieve the best accuracy.

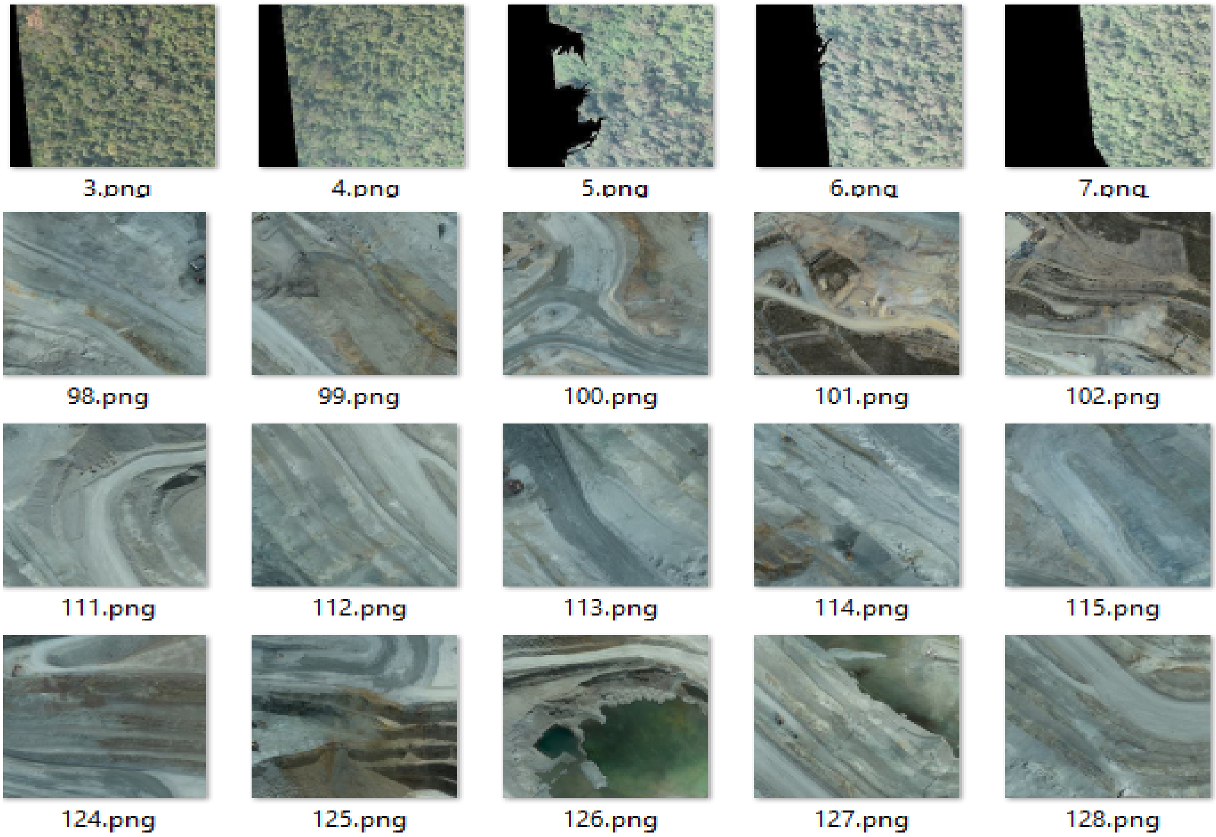


Figure 5 Cropped images to 256 pixels

4.3 Model description

4.3.1 Input/output data

The input data for the neural network consists of a four-channel packet: RGB (colour channels) and the cosine field. The output is represented by four channels that correspond to the probability of predicting four different classes:

- Background.
- Bench.
- Flat part of trees.
- Sloped part of trees.

This class structure allows the model to differentiate between sloped benches and sloped parts of trees. We added the bench class to help the model learn the difference between benches and trees. As a result, the model can better detect the sloped edges of trees compared to benches, even if they are both green.

4.4 Neural network architecture

A neural network was implemented using the UNet architecture, which is based on the 'efficientnet' backbone. UNet is a well-known architecture used for semantic segmentation that was originally developed for biomedical image segmentation. The architecture includes connections between layers at the same depth, allowing the model to establish meaningful relationships between the input and output data.

Efficientnet is a state-of-the-art backbone architecture that offers different complexity levels (B0..B7).

Since our model predicts multiple classes for semantic segmentation, the output layer uses the 'softmax' activation function.

Figure 6 shows CNN with UNet architecture implemented for this task.

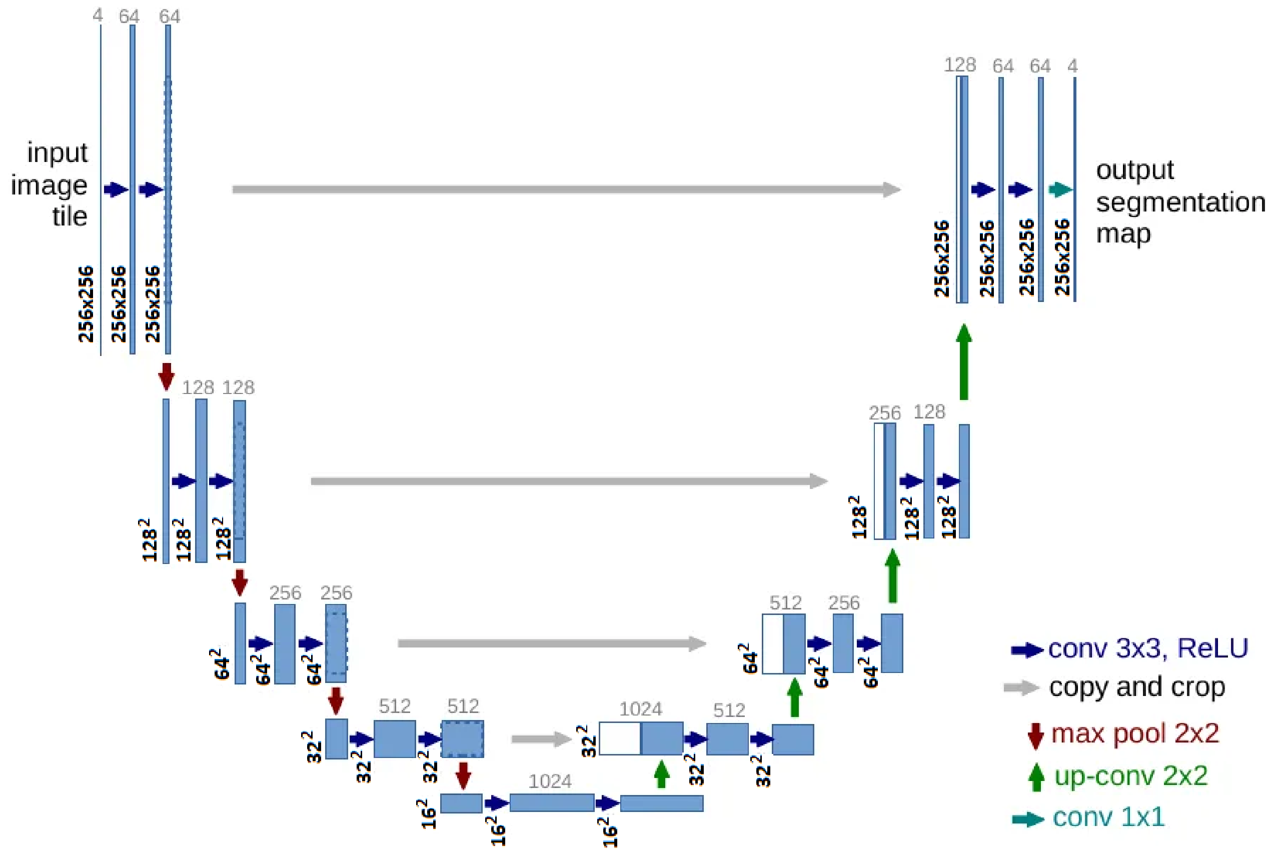


Figure 6 Diagram displaying CCN with UNet architecture

4.5 Model training

The following sections describe the process undertaken for training of the AI model.

4.5.1 Data augmentation

To increase the variety of training data we applied augmentation techniques to the source dataset. Each time a source patch was used in the training pipeline it underwent a series of random transformations, such as horizontal/vertical flip, rotation, scaling, shifting, brightness/contrast adjustment, colour distortion and adding Gaussian noise. These transformations help prevent overfitting and improve accuracy.

4.5.2 *Measuring the model performance: optimiser, metrics, loss function*

We used the Adam optimiser with a learning rate of 5e-4. The metrics used to evaluate the model's performance were intersection over union (IoU), F1 score and F2 score. The loss function used was the categorical focal loss, which is based on binary focal loss. Figure 7 displays loss and metrics history during training of the AI model.

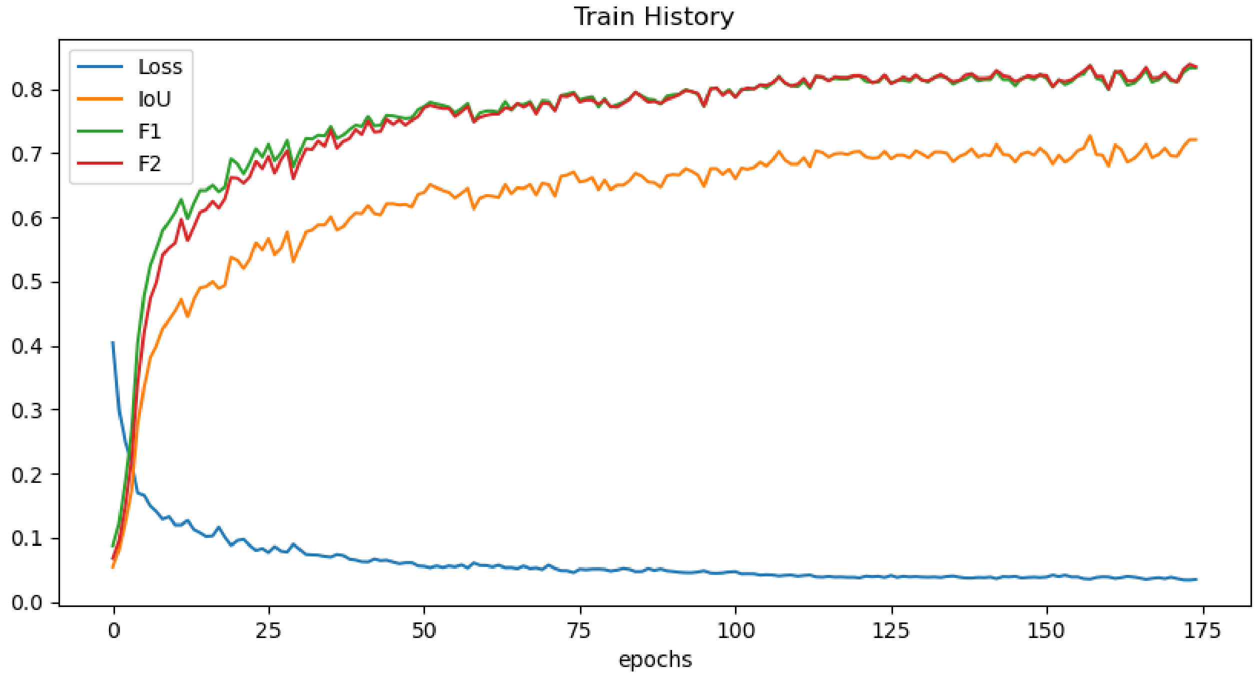


Figure 7 Loss and metrics history during training of the AI model

4.6 Inference pipeline

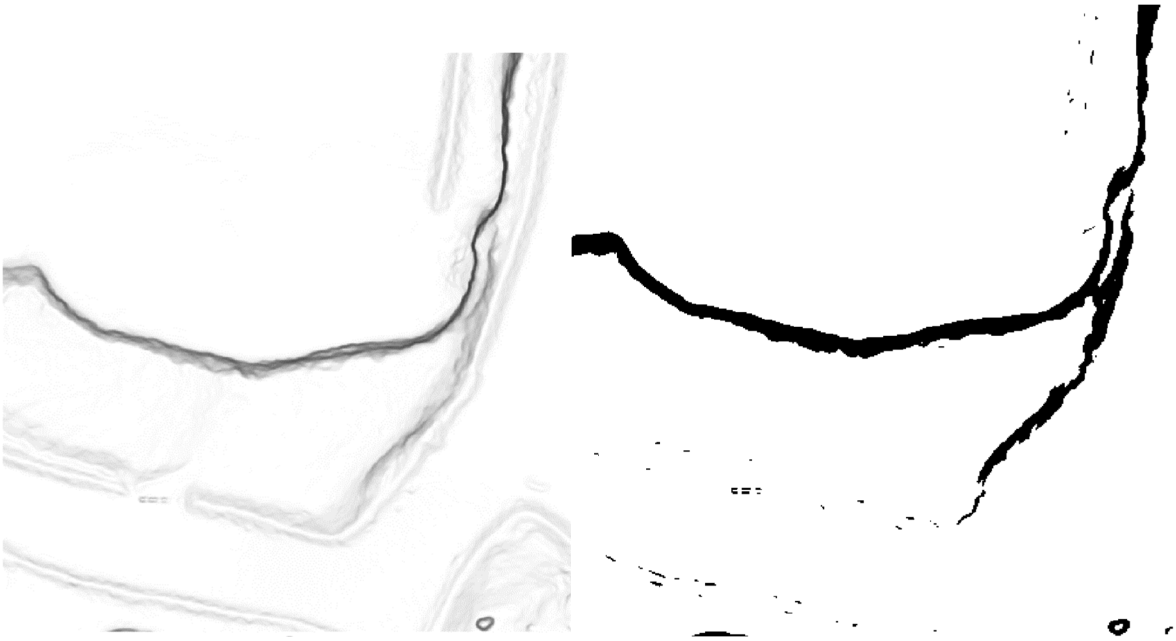
To ensure accurate predictions, the input image is divided into patches and predictions are made for each patch. However, predictions near the patch boundaries may have large errors. To address this, we used overlapping patches and merged them into one large image.

After tree and object filtering is undertaken, a computer vision algorithm is employed to detect crest-toe lines by processing the image pixel by pixel in the DSM.

The steps undertaken during the process are as follows:

- Detecting the 3D-field of normals from the DSM.
- Calculating the slope cosine from the normals.
- Filtering the slope cosine field based on a threshold angle (Figure 8).
- Removing small islands and holes from the filtered mask.
- Expanding the mask boundaries to capture more flat top and bottom surfaces (see Figures 9 and 10).
- Suppressing trees using a CNN with a UNet architecture.
- Smoothing the boundaries (Figure 11).
- Creating centrelines by skeletonising the resulting mask (Figure 12).
- Connecting crest and toe lines for each skeleton centreline (Figure 12).
- Integrating complex areas to obtain crest-toe pairs.

- Merging the raster mask and result edges (Figure 13).



(a) (b)

Figure 8 Filtering and masking of the slope cosine field based on a threshold angle. (a) Slope cosine field. 1-vertical, 0-horizontal; (b) Mask where cosine less than threshold

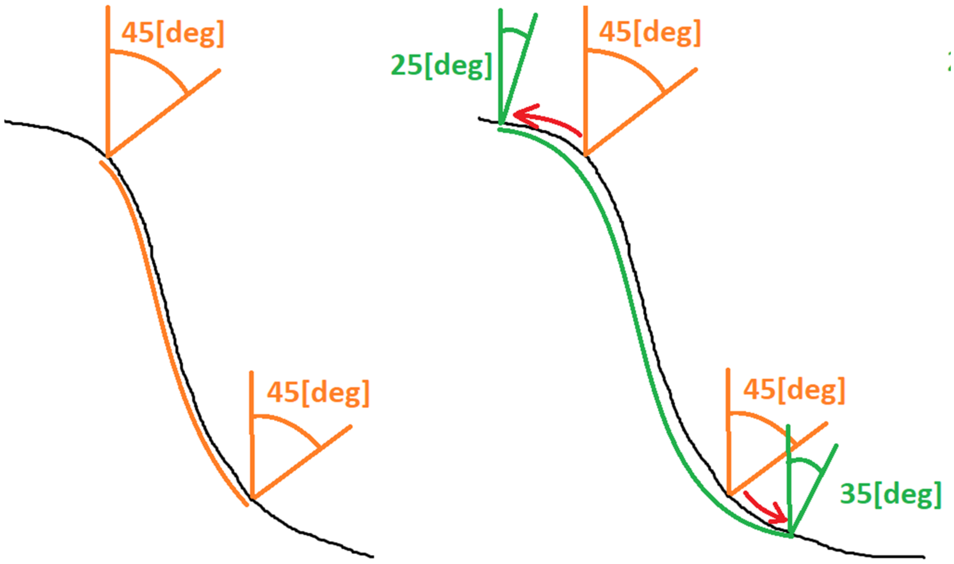


Figure 9 Slices through the model (pit geometry) to display growth of the boundary to capture more of the flat top and bottom boundaries of the model

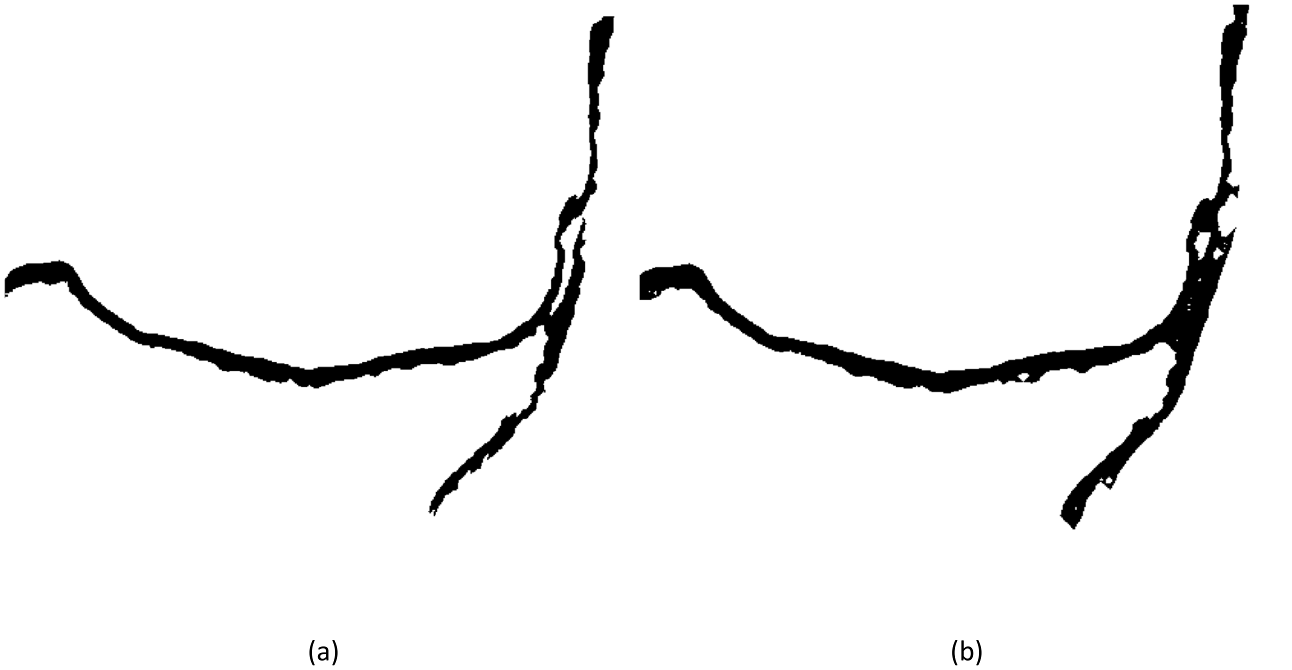


Figure 10 Masking increased 25–55°, with effect on predicted identification of berm or flat areas in the model. (a) Filtered mask; (b) Mask raised up to 25 [deg] and down to 55°

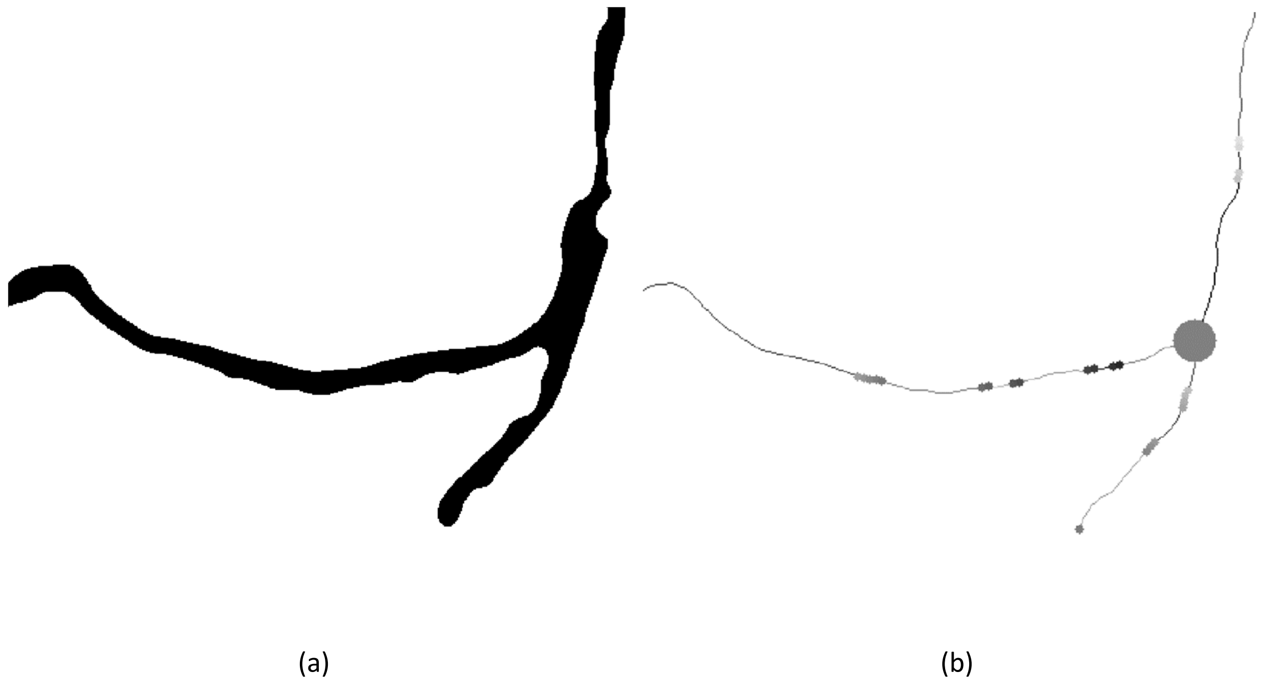
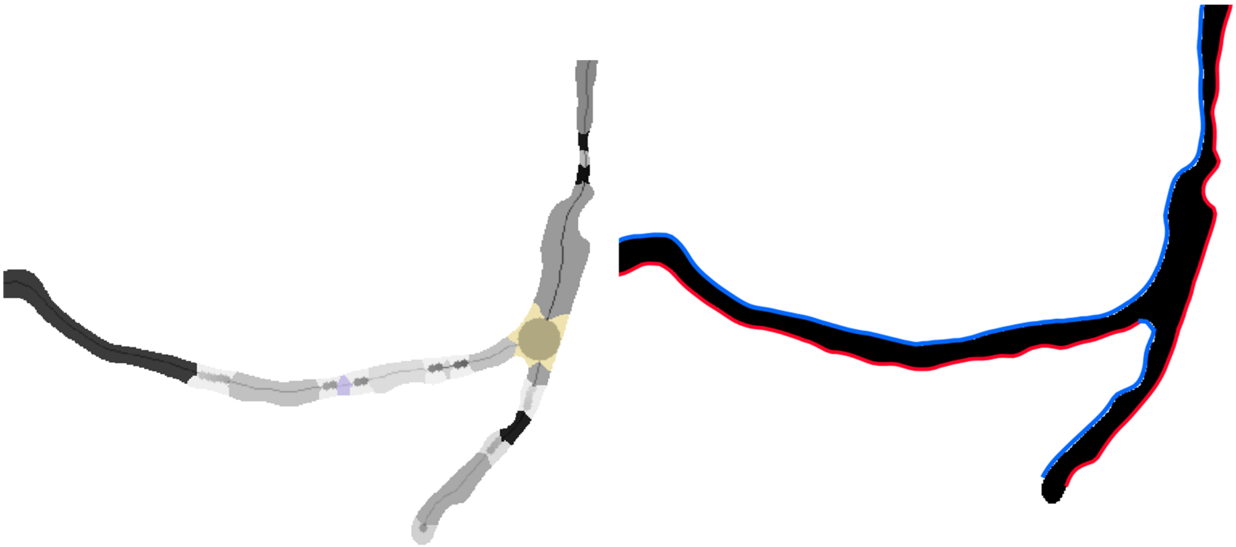


Figure 11 Smoothed boundaries within the raster mask, and subsequent generation of the centrelines creating a vectorised topography. (a) Finish state of the raster mask; (b) Centrelines graph with circles in lines ends



(a) (b)

Figure 12 Display of integration following connection of crest and toe lines for each skeleton centreline and formation of crest and toe pairs. (a) Raster topological separation by graph. Not shared contour lines are crest or toe lines; (b) Merge of raster mask and result edges

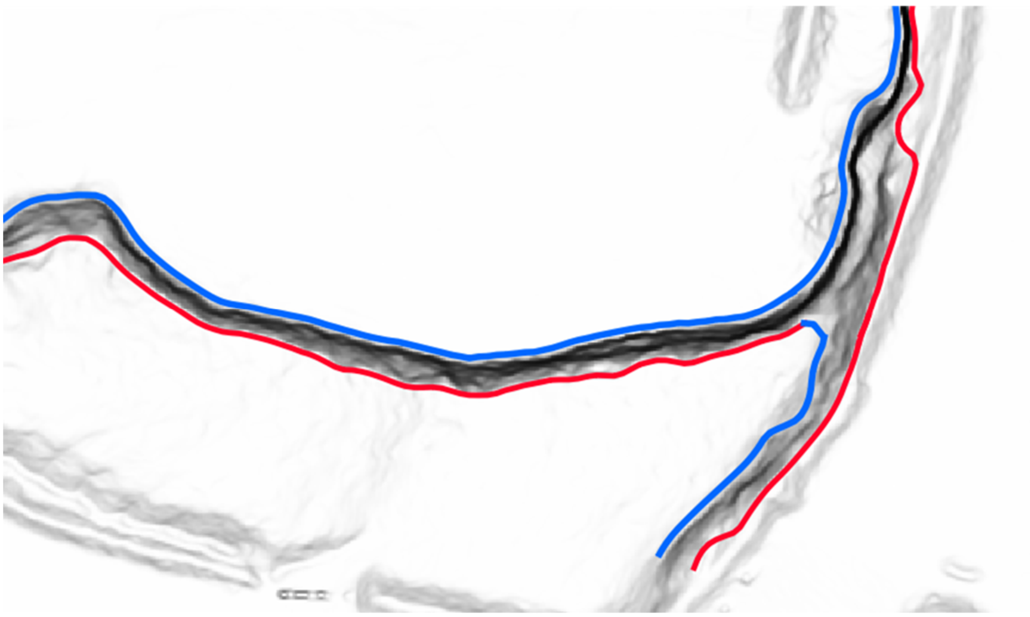


Figure 13 Final product displaying merging of the raster mask and the resulting edges (crest and toe lines)

5 Traditional versus AI-based pit reconciliation

In this chapter we delve into a comprehensive investigation that aims to uncover any disparities between manually selected crest and toe points and those identified by the AI software in the context of geotechnical analyses. The accurate determination of these critical points plays a pivotal role in open pit reconciliation, and is an important step in validation of the AI model. It also provides the opportunity to continue training and therefore refining the AI model for future iterations of the software development.

The primary objective is to rigorously compare the accuracy levels achieved by AI software against the traditional manual selection process. We analyse the results obtained from both approaches, shedding light on the trade-offs between precision and efficiency. By quantifying the discrepancies in accuracy and assessing the time required for data collection, we provide valuable insights into the level of effort involved in point identification and data representation for reconciliation.

Furthermore, this chapter highlights the current limitations and challenges associated with utilising AI software for point selection in reconciliation. We explore factors such as dataset quality, algorithm robustness and the interpretability of AI-driven results. Understanding these limitations is crucial for assessing the reliability and applicability of AI technologies in real-world scenarios.

One key aspect of our analysis focuses on the time taken to produce crest and toe points using the manual method versus AI-driven approaches. By conducting controlled experiments and meticulously recording the time spent on each process, we present a clear comparison that demonstrates the potential time-saving benefits of employing AI software in geotechnical data collection.

5.1 Method of analysis

Two trial areas were selected in hard rock open pit mines within an existing database of photogrammetrically modelled open pits. An area approximately 100 m in length and two benches in height was selected at each mine site for conducting reconciliation of crest and toe positions (see Figure 14).

For each section of wall, the AI-based software platform Strayos was used to generate crest and toe lines. The process was then conducted manually.

In order to generate crest and toe lines manually, the 3D digital model was sliced in increments of 1 m, and the crest and toe positions were digitised as points. After stepping through each 1 m-thick slice and digitising crest and toe points, a stringline connecting each point to form the crest and toe lines was manually digitised.

Sectioning and digitising the model on 1 m sections and digitising the toe and crest lines was found to be very time-consuming. The process was re-run manually based on 5 m-spaced sections to speed up the process. It was later found through our analysis that this resulted in minimal reduction in accuracy of the reconciliation process.

Once crest and toe picks were determined both through the AI process and manually, the resulting lines were compared. The method of comparison was by measurement of the horizontal and absolute distances from the actual toe or crest pick to the design (see Figure 15).

Defining of the crest from the as-built physical model is a relatively straightforward process, however, the pick of the toe position can be subjective due to gradual flattening of the wall. It is generally accepted that the transition from toe position to catch berm is at the point when the slope becomes flatter than 20°. If the wall is steeper than this, then a falling rock will not be arrested.

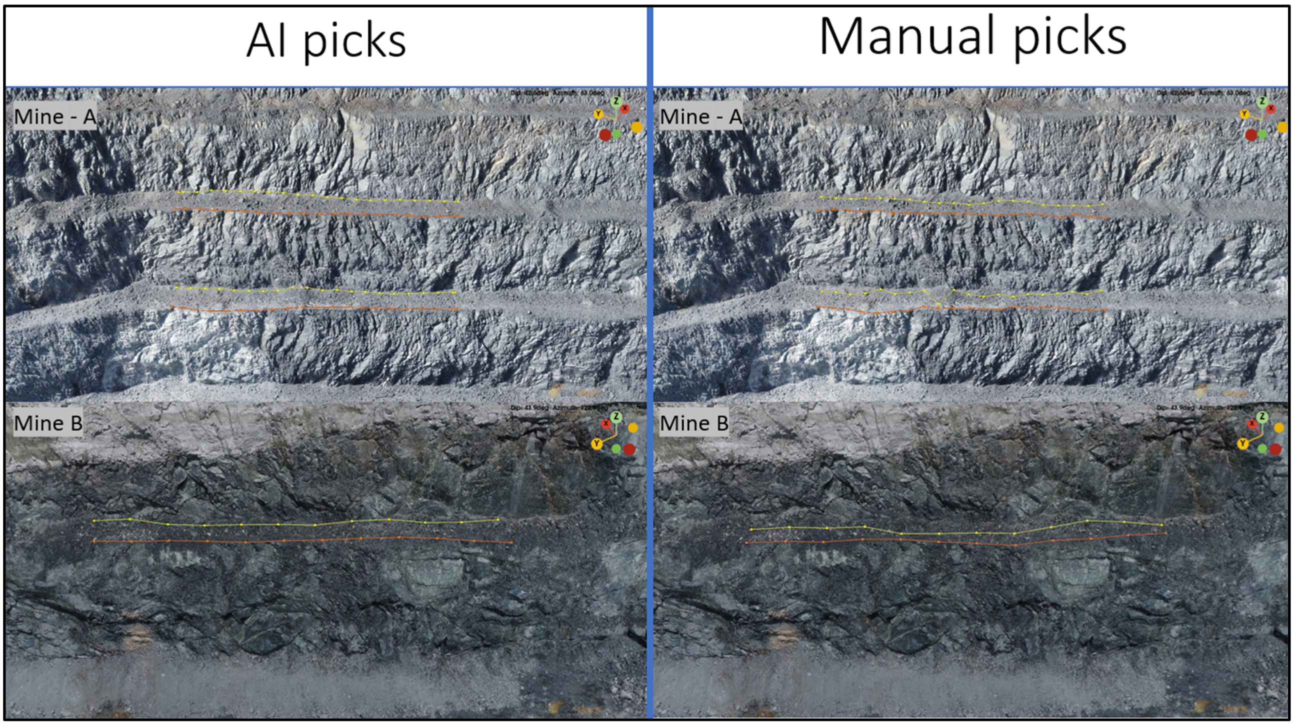


Figure 14 AI-generated and manually generated crest and toe picks for two separate mines

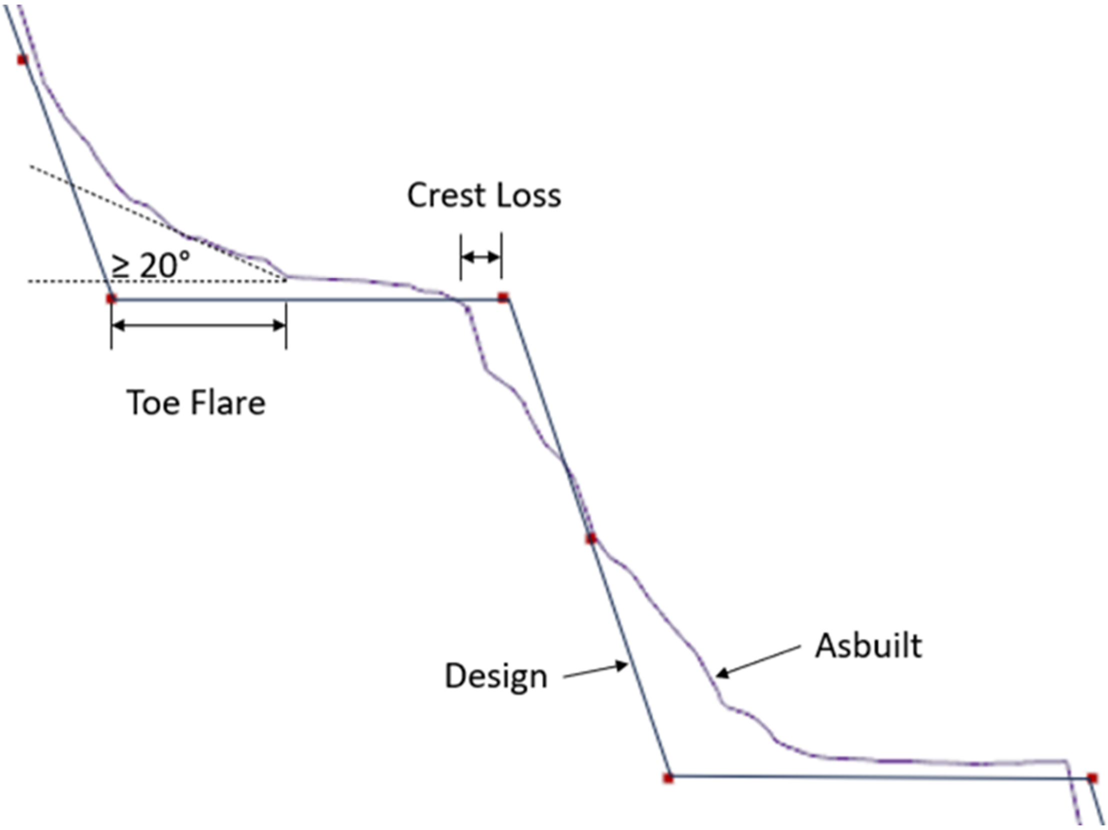


Figure 15 Defining crest loss, toe flare and the point at which the berm is flat enough and is considered to have catch capacity

5.2 Results and discussion of results

For each of the selected areas within the pits, the AI-generated and manually derived crest and toe picks were compared graphically and then statistically. When comparing AI-generated and manually picked crests (Figure 16) and toes (Figure 17), it was found that, in general, AI-generated and manually picked crests align very closely across both Mine A and Mine B, and across multiple benches. However, this was not the case for the toe picks. It was found that generally a large disparity existed with the toe picks generated from AI compared to the manually generated pick.

Furthermore, it was also found that AI-generated crest and toe lines are much smoother when compared to the manually generated crest and toe lines. The reason for the level of smoothing is currently being investigated further. Manually picked crests generally appear more jagged as the crest line is precisely followed, and local failure mechanisms such as wedge failures can be clearly identified by the rapid change in the gradient of the line.

The difference between AI-generated and manually picked toe positions is significant, and can be traced back to the definition of the point at which the toe becomes flat enough to be considered as the catch berm and is no longer the batter. The AI appears to place the toe line at the interface between the sub-vertical batter and the point at which flaring becomes evident (or, the toe). When picked manually, the user measures the point at which the toe becomes flatter than 20°, at which point is it consider to be the catch berm.

During the writing of this paper, the AI platform (Strayos) was undergoing further developments to make the toe selection a user-defined option.

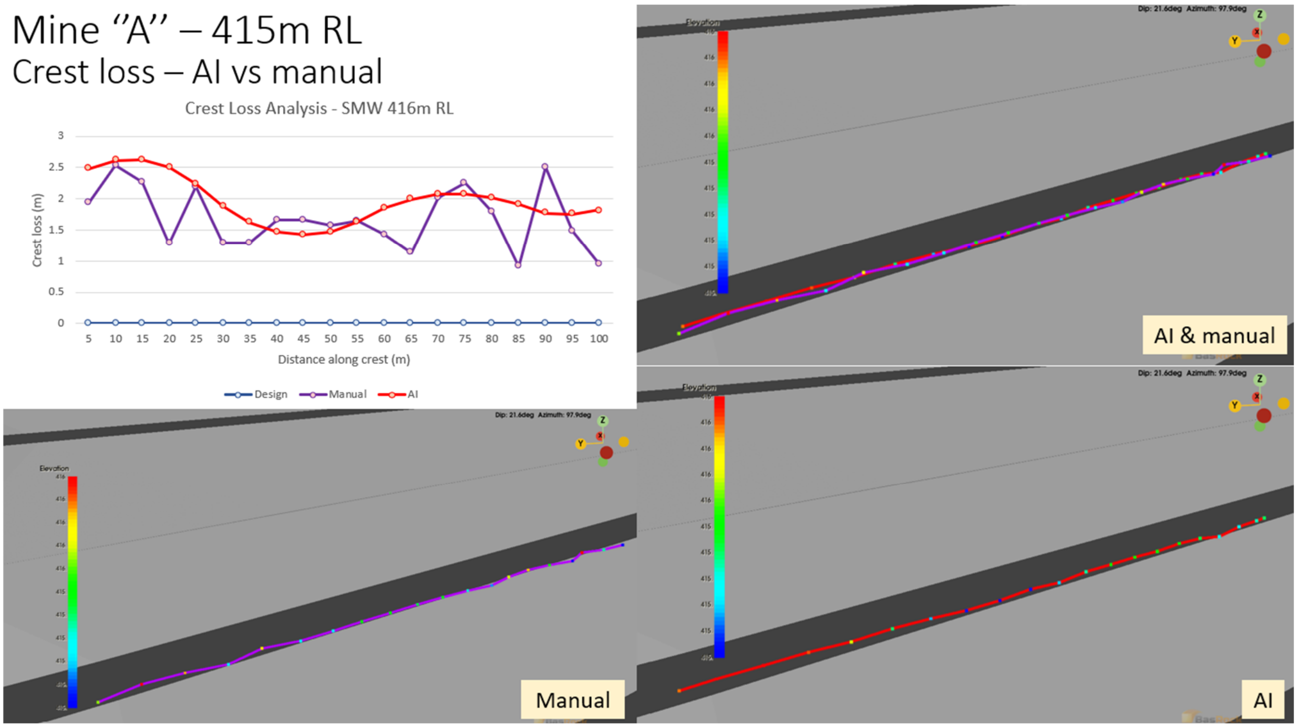


Figure 16 Comparison of an AI-generated versus manual pick of the crest for Mine A – 415 m RL

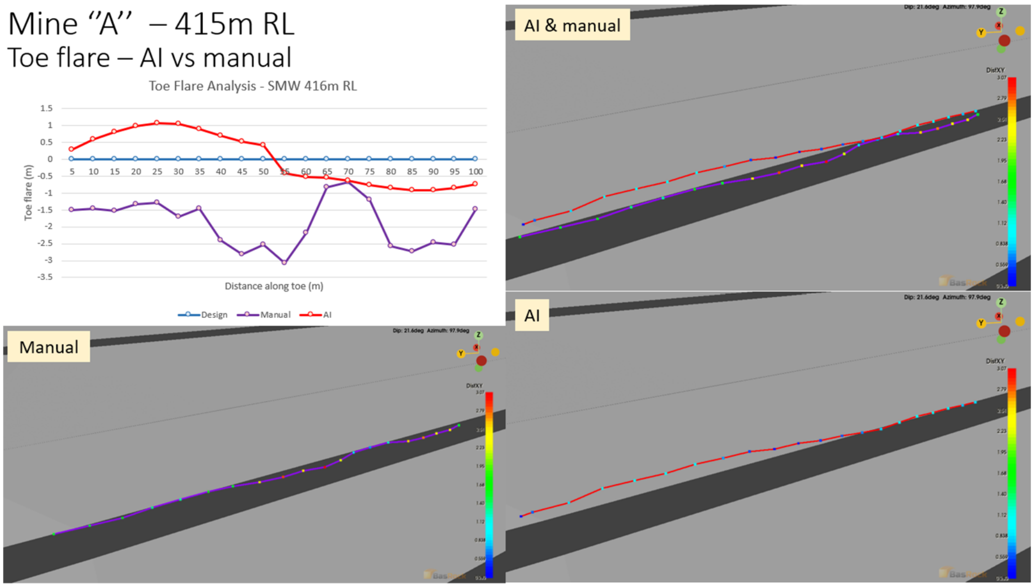


Figure 17 Comparison of an AI-generated versus manual pick of the toe for Mine A – 415 m RL

When comparing the AI- and manually generated crest picks, the crest lost was analysed by looking at mean, standard deviation, minimum, maximum and confidence levels (percentile values) for comparison, as well as visual assessment of the actual crest against the designed crest position. It was found that AI-generated toe picks are generally very similar to the manually derived toe picks. It should also be noted that picking of the crest or toe can be a subjective process and may vary slightly from person to person. Therefore, utilising AI offers a consistent approach with human bias removed. However, bias may still exist in the way the AI model for picking crest and toe has been trained.

When comparing manual and AI crest loss picks for three separate sets of data (Tables 2, 3 and 4), it was observed that, in general, the AI-picked crest position indicated greater crest loss had occurred than was observed with the manual pick. Interestingly, the minimum point of crest loss was always observed to be greater within the AI-generated data. The maximum point of crest loss was greater in two of the three cases of AI-generated data.

Table 2 Summary statistics and percentile values comparing manually picked and AI-picked toe positions (crest loss) for Mine A 415 m RL

Percentile	Manual (m)	AI (m)	Difference (m)	Difference (%)
P25	1.3	1.7	0.4	30.1
P50	1.7	1.9	0.3	11.8
P75	2.1	2.1	0.0	0.0
P95	2.5	2.6	0.1	4.0
Summary statistics				
Mean	1.7	1.9	0.2	11.8
Standard error	0.11	0.08	0.03	
Median	1.7	1.9	0.25	11.8
Minimum	0.9	1.4	0.5	55.6
Maximum	2.5	2.6	0.1	4.0

Table 3 Summary statistics and percentile values comparing manually picked and AI-picked toe positions (crest loss) for Mine A 390 m RL

Percentile	Manual (m)	AI (m)	Difference (m)	Difference (%)
P25	3.1	3.4	0.3	9.7
P50	2.7	3.1	0.3	14.8
P75	1.6	1.8	0.2	12.5
P95	0.3	0.8	0.5	166.7
Summary statistics				
Mean	2.4	2.5	0.1	4.2
Standard error	0.25	0.23	-0.02	
Median	2.7	3.1	0.4	14.8
Minimum	0.1	0.6	-0.5	-12.2
Maximum	4.1	3.6	0.5	600

Table 4 Summary statistics and percentile values comparing manually picked and AI-picked toe positions (crest loss) for Mine B 140 m RL

Percentile	Manual (m)	AI (m)	Difference (m)	Difference (%)
P25	3.8	4.1	0.3	6.4
P50	3.5	3.8	0.3	7.8
P75	3.2	3.7	0.5	13.1
P95	2.8	3.6	0.8	22.4
Summary statistics				
Mean	3.5	3.9	0.4	11.4
Standard error	0.14	0.06	-0.08	
Median	3.5	3.8	0.3	8.6
Minimum	2.6	3.6	0.1	2.5
Maximum	4.0	4.1	1.0	38.5

In terms of the effort required to undertake both types of analysis, the AI-based approach is superior. The AI-based approach can generate crest and toe lines in a matter of seconds, whereas a ~100 m section of a single berm can take between 30 and 40 minutes for slicing, digitising crest and toe positions every 5 m, digitising a stringline representing both the crest and toe locations, and then manually measuring the distance between the as-built and the design.

AI offers the opportunity to analyse significant larger areas of open pits in a fraction of the time it takes to complete the same work manually.

6 Conclusion

This paper sought to highlight the under-utilisation of data captured in mine sites and the potential for AI to enhance operational decision-making and workflow efficiency. While a small percentage of available data is currently used to its full capacity, leveraging data effectively can lead to improved mining practices, decision-making and, therefore, mining outcomes. However, to implement meaningful changes there is a need to streamline workflows, optimise resource utilisation and leverage the tools available in the industry.

The use of UAVs for aerial survey data capture, coupled with advanced photogrammetric modelling or LiDAR scanning, offers a reliable and accurate approach to generate detailed and high-resolution models of open pit mines. This data can be used to validate as-built pit designs, ensuring compliance with engineering specifications and improving safety and operational efficiency.

Open pit reconciliation, specifically the determination of crest and toe points, plays a critical role in ensuring compliance and assessing performance. By comparing manually selected points with those identified by AI software, disparities were observed, particularly in toe picks. AI-generated crest and toe lines demonstrated consistency across multiple benches and mines, but further investigation is needed to understand the reasons for the observed smoothing effect.

The comparison between manual and AI approaches revealed that AI picks indicated higher crest loss on average, with the minimum point of crest loss consistently higher compared to manual picks. Additionally, AI-assisted workflows showed significant time savings, generating crest and toe lines in seconds compared to the time-consuming manual process.

While the results highlight the potential of AI in open pit reconciliation, it is essential to address the subjective nature of toe picks and potential biases in the AI model. Further refinement and development of AI-assisted workflows are needed to ensure reliable and accurate results.

The incorporation of UAVs, advanced data processing software and AI models allows for rapid and consistent data capture and analysis. This facilitates improved safety, compliance and efficiency in open pit mining operations. The ability to identify geotechnical hazards, assess rock mass and structural response, quantify changes in excavation practices and track long-term performance contributes to informed decision-making and optimised pit designs.

In conclusion, AI-assisted workflows have the potential to revolutionise open pit mining by harnessing the power of data and automation. However, ongoing research and development are necessary to address limitations and improve the reliability and interpretability of AI models. By embracing these technologies, mines can unlock the true value of their data, leading to safer, more efficient and economically viable operations. Furthermore, collaboration between multi-disciplined teams is essential to harnessing the benefit of adopting technology into mining and reconciliation processes.

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