Using Artificial Intelligence for Roof Fall Hazard Identification in Limestone Mines

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INTRODUCTION

Roof falls: Fall of ground from above in mining/tunneling operations due to geological reasons.

Figure: Roof fall causing equipment damage. (Source: US Department of Labor)

- Roof falls have been responsible for the significant portion of the accidents in underground mines. These accidents cause fatalities, injuries, damages to the equipment and lost time.
- Roof fall hazard assessment techniques proposed in the literature and practiced by the industry, largely depend on visual observations and expert opinion.

OBJECTIVE

Transfer of expert judgment on roof fall hazard identification to a computer system for future hazard detection without an expert.

Motivations:

- Protect ground control personnel from safety risks during hazard inspections.
- Prevent inadequate hazard inspections during personnel change caused by the difficulty of transferring knowledge between personnel since the judgment is intuitive.
- Contribute to the transition to autonomous mining operations by developing an autonomous hazard inspection tool.

BACKGROUND

Case Study: Underground Limestone Mine in Midwestern U.S.

- Roof hazard conditions are assessed by visual inspections and knowledge gained through observational techniques. Near-failures are usually detected by sounding.
- V-shaped features caused by high horizontal stresses on the mine roof are used as indicators of hazardous roof conditions by ground control personnel at the mine.

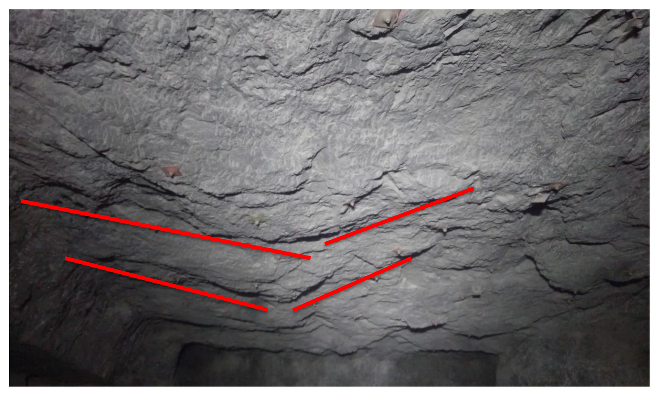


Figure: V-shaped features on the mine roof

- Smoother roof surfaces are observed where the roof conditions are non-hazardous.
- Experts stated that they use **depth** and **frequency** of the V-shaped features to determine the hazard level.
- Image data has a promising potential in developing an autonomous hazard detection system since the current roof fall hazard assessment techniques depend on visual clues.
- Development of a convolutional neural network system that classifies roof fall hazard levels based on roof images is explained in this poster.

METHODOLOGY

Step I. Determination of Roof Fall Hazard Levels

- Ground control personnel kept records of V-shaped features and drew them on the mine map.

- Relationship between V-shaped features and previous roof falls is shown by using the mapped features around previous roof fall locations and randomly selected non-roof fall locations.

Location of No-roof falls

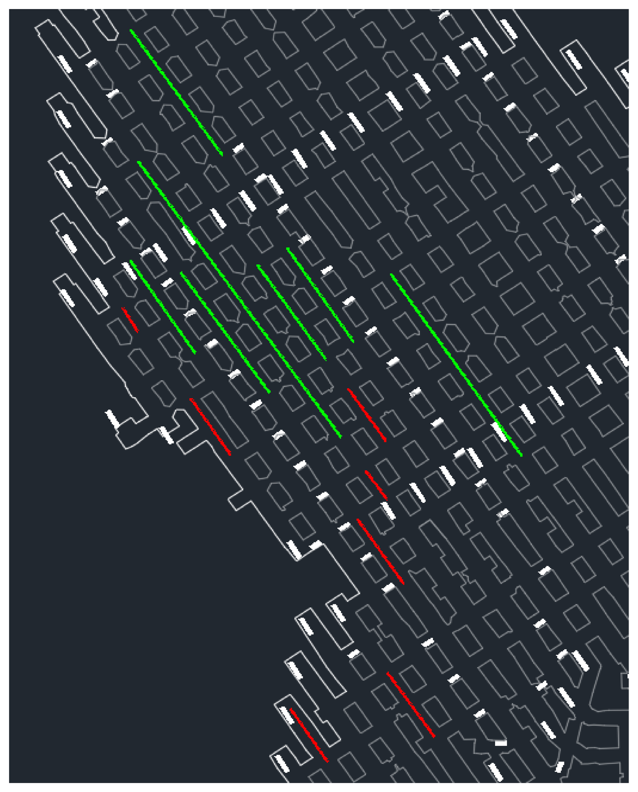
Location of Roof falls

- A circle with a radius of 30 ft is drawn around each roof fall and no roof fall location. Number of chevron features inside each circle and the average depth of the features inside each circle were recorded.

	Frequency	**Depth**
P-Values	0.00006	0.02

- The difference between V-shaped features (frequency and depth) around roof fall locations and V-shaped features around no-roof fall locations is unlikely to occur by chance. It is therefore plausible that the frequency and depth of V-shaped features could be used as indicators of a roof fall hazard.

Step II. Data Collection



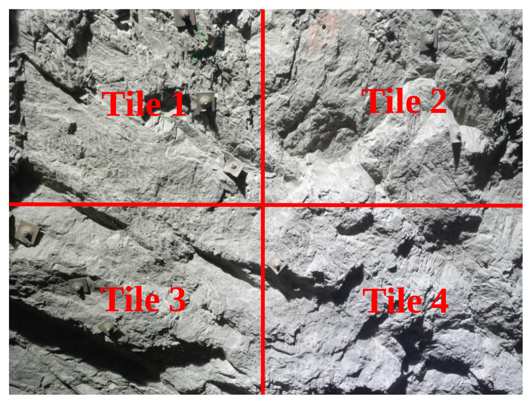
Hazardous Roof

Non-hazardous Roof

- Hazardous and non-hazardous roof locations are selected based on discussions with ground control experts in the mine.
- The difference in hazard levels between selected hazardous and non hazardous roof locations demonstrated by comparing the frequency and depth of V-shaped features.

- Using the mine map, the number and the average depth of the V-shaped features were recorded. A statistical t-test is done to see if there is a significant difference between selected hazardous and non-hazardous data collection locations.
- P-Values: Frequency: 0.0005, Depth: 0.016
- The difference between V-shaped features around expert-categorized hazardous and non-hazardous locations is statistically significant, confirming frequency and depth are related to human identified hazards.
- Images are obtained using a Nikon D5000 camera in the selected locations.

Step III. Image Pre-processing



- The number of images quadrupled by tiling.
- Data augmentation is used in order to artificially increase the number of images seen by the network (random rotation, random flip, changing brightness or saturation).
- Images are resized to 224 x 224.

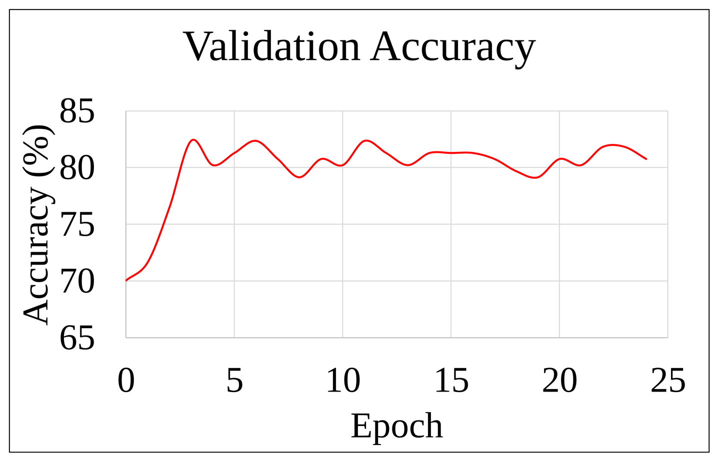
Step IV. Development of Convolutional Neural Network (CNN)

- The CNN is developed using a transfer learning approach. The transfer learning uses a model trained on a large dataset and then transfers its knowledge to solve another problem with a smaller dataset.
- Pre-trained model used in this study is trained with the ImageNet dataset that contains 1.2 million images with over 1000 categories. ResNet CNN architecture is used.

Input Dataset

	Hazardous	Non-hazardous	Total
Training	249	505	754
Validation	63	125	188
Total	312	624	

RESULTS



- The highest classification accuracy achieved is 82.4% with using batch size as 16.

Confusion Matrix

		Predicted	
		Hazard	Non-Hazard
Actual	Hazard	43	20
	Non-hazard	13	112

- The confusion matrix shows that the model successfully classifies non-hazard images.
- However, only 68% of hazard images were successfully labeled by the model. The reason behind the high number of false positives might be the higher number of non-hazard training data which results in the model's tendency to classify in favor of the non-hazard class.

CONCLUSION

- The AI system has the potential to supplement roof fall risk management procedures by providing accurate hazard maps without putting personnel at risk.
- The limitation of the system is that it can only be as good as the expert.

Future work;

- Further data collection to improve the quantity of hazardous roof condition images.
- Analysis of image textural features (e.g. linear features, edge detection, blob areas) in order to improve dataset by adding these as additional bands.
- Utilization of deep learning interpretability methods to investigate which physical features inside the image AI system takes into account during classification.