24-033

Enhancing Robotic Perception for Autonomous Roof Bolting Using an Event Based Machine Learning Framework

Akram Marseet
M3 Robotics Lab

Rik Banerjee
M3 Robotics Lab

Andrew J. Petruska
M3 Robotics Lab

ABSTRACT

Underground mine roof bolting is a crucial operation for miners' safety and mine sustainability. Since roof bolting is a manual or human-supervised operation, miners' safety is at risk due to dust or rock falls. Traditional machine learning algorithms have shown limitations to detecting drillable areas, mainly due to harsh lighting conditions. The authors propose an adaptive deep-learning framework for autonomous roof bolting. The proposed framework is based on implementing a binary semantic segmentation algorithm on color images to classify pixels that belong to rock from those that belong to non-rock. Significantly, the proposed framework implements deep learning semantic segmentation on images from traditional and neuromorphic vision sensors in underground mines. The performance of the proposed model shows an impressive accuracy level of at least 98% at a low number of training epochs with smooth learning curves. The high accuracy enables the implementation of autonomous roof bolting, greatly improving miners' safety and operational efficiency while reducing human exposure to safety hazards. This research will advance the use of deep learning in mining automation and has the potential to revolutionize the traditional mining industry.

INTRODUCTION

The Mining sector plays a pivotal role in the development of the world economy [1], [2]. Underground mining is growing due to the rising demand for minerals for industries such as the automotive industry and clean energy technologies [3]. Due to the rapid demand for minerals, the mining industry is moving toward deep underground mining [4]. Nonetheless, underground mining presents significant challenges across various dimensions [5]. Human safety is one of the main challenges in underground mining [6], mines sustainability [7], and working conditions [8] also contribute to other challenges in underground mining environments. According to a report issued by the United States Mine Safety and Health Administration (MSHA), the total number of fatal injuries till the third quarter of 2023 is higher than that for the previous year [9].

One of the hazards in the underground mining industry that causes fantails and serious injuries is falls on the roofs and the ribs of the underground mines. [10]. According to MSHA, 26 fatal injuries have been reported as of August 5th, 2023 [11]. Roof fall hazards are addressed by roof bolting [12] which has been recognized by the Coal Mine Health and Safety Act of 1969 as the exclusive method of providing support for underground entry [13]. Roof bolting is a fundamental technique for ensuring the safety and stability of underground mine environments, particularly in areas where roof conditions are unstable or prone to collapses [14]. Roof bolting is still an active research area where there are many aspects that need to be addressed including safety during roof bolting and increasing the efficiency of the roof bolting process. Roof bolting processes mainly include perforating the unsupported roof, followed by the insertion of a roof bolt and epoxy resin to fasten the overlying roof strata [15]. For rock support, straps are used [16]. Therefore, an additional step is added which is drilling through holes in the straps.

Although roof bolting improves the safety of mine personnel and the sustainability of mines, the roof bolting process is risky on roof blotters. There are safety hazards

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associated with roof bolting process on roof bolters including fatal and nonfatal injuries [17]. The fatal and nonfatal injuries associated with roof bolting are caused by six tasks with the following risk indices: bolting, handling of materials, temporary roof support, drilling, tramming, and traversing [18]. Airborne dust exposure is also a health hazard associated with roof bolting which has not been addressed jointly with the previous safety hazards in the literature [19].

Based on the safety risks of roof bolters during roof bolting operations and based on a recommendation by the National Institute for Occupational Safety and Health (NIOSH), the authors conduct this research to improve the safety of roof bolters by proposing a computer vision-based machine learning model to automate roof bolting which will save roof bolters and reduces the cost.

MACHINE LEARNING FOR ROOF BOLTING

The application of machine learning in the mining industry is still growing compared to other fields [20]. Leveraging machine learning in the mining industry is essential in driving the mining industry to be an autonomous and more technologically advanced sector [21]. Deep learning is a subfield of machine learning that enhances the performance of machine learning algorithms especially in computer vision-based tasks. Autonomous technologies in the mining industry offer numerous advantages by minimizing workers' exposure to dangerous conditions, increasing safety standards, lowering costs, and enhancing efficiency [22]. An autonomous system needs to understand the scene and localize objects of interest. Therefore, the first task to automate roof bolting is the perception task to classify rocks from non-rocks and locate where to drill. Manual methods are still used for the localization of bolts in underground roof bolting [23]. In the literature [23],[24], researchers used machine learning algorithms to detect roof bolts that have been already installed. However, none of the existing work has addressed the automatic detection of where to drill the holes for roof bolting. The automation of the roof bolting process using machine learning requires the detection of rock from anything that is non-rock such as power cables of existing straps. Figure 1 shows a scenario of the working environment where it is required to identify rock areas from a strap and a power cable. In addition, it is required to identify the small holes inside the strap to drill and insert the bolts.

Computer vision tasks are mainly classified into image classification, object detection and recognition, and image segmentation. However, one of the key challenges for computer vision tasks in underground mines is the poor lighting conditions and the dust which degrade the quality of images. As a result, the performance of the machine learning algorithm is degraded. Prepossessing for image enhancement can be used to improve the performance of deep learning algorithms [25]. Image pre-processing is also useful for unsupervised domain adaption where a deep learning model that has been trained on images captured by traditional cameras (also known as frame-based cameras) can be used for sparse images captured by event-based cameras. In this research, deep learning-based binary image semantic segmentation is used to classify pixels that belong to rocks from pixels that belong to non-rock objects as the first step toward autonomous roof bolting. Figure 2 shows a sample of a color image and its corresponding segmented mask.

Figure 1. A scenario of rock, strap, and power cable area in the Edgar Mine in Idaho Springs, CO where it is required to identify the drillable regions from non-rock regions

EVENT CAMERAS

Event cameras are bio-inspired cameras that capture the changes of pixel intensity asynchronously as a stream of events instead of collectively at fixed frame rates which are streamed by regular cameras. An event $e(x, y, t)$ as

$$e(x, y, t) = \begin{cases} 1, \Delta_L(x, y, t) > 0 \\ -1, \Delta_L(x, y, t) < 0 \\ 0, \Delta_L(x, y, t) = 0 \end{cases} \quad (1)$$

where $e(x, y, t)$ is the event value of a pixel located at (x, y) at timestamp t and $\Delta_L(x, y, t)$ is the change of the pixel's intensity between $t - 1$ and t. Event cameras are characterized by high dynamic range, high temporal resolution, and low blur for fast motion [26]. The high dynamic range

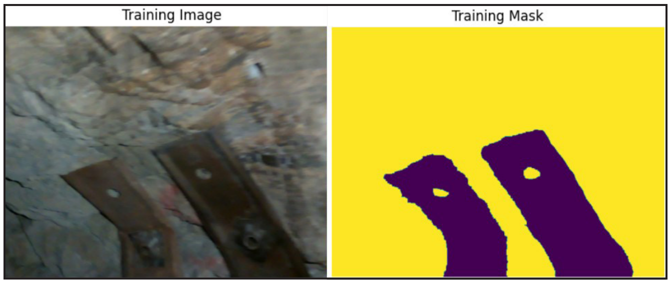


Figure 2. A Training image with its corresponding ground-truth training mask in Edgar Mine in Idaho Springs, CO. This pair of images form the training image and the training label for the proposed semantic segmentation model which will produce a segmented image (image) for a given color image

property arises from the circuitry of the event camera which outputs the pixel intensity on a logarithmic scale. The high temporal resolution arises from event cameras stream of events instead of the whole frame. Due to these properties, event cameras are capable of responding to intensity changes of the scene when the object is moving fast, which means that event images almost do not suffer blur due to fast motion. This type of vision sensor is aimed to be used to overcome the issues in environments with poor lighting and airborne dust as in underground mines. The principle of operation of event cameras is based in dynamic scenes in which the object of interest is moving, the camera is moving, or the lighting conditions is changing. Figure 3 shows two types of images that have been captured by an event camera. Because images from event cameras differ from images from regular cameras, existing deep learning algorithms cannot be implemented directly to event-camera data driven tasks. In addition, there is no enough training data for event images especially in underground mining environments [27].

The main contributions of this research are:

- Building a deep learning-based binary image semantic segmentation for underground roof bolting using color images.
- Adapting the deep learning model to be able to implement binary semantic segmentation for both types of images; images from regular cameras and imaged from event cameras.

PROPOSED MODEL

The proposed model is based on formulating the autonomous roof bolting process as a binary model where the goal is to classify the seen into two regions, rock regions or non-rock regions. Among the three main tasks in computer vision, image semantic segmentation is the most appropriate method to classify rock areas from any non-rock areas. Image segmentation using deep learning convolutional neural networks model is promising to provide a high accurate segmentation model. The authors selected to use a deep learning convolutional neural network based image segmentation model called Unet [28]. Unet is a convolutional neural network-deep learning model which is used for semantic segmented. The training data are images (color) while the training labels are labeled masks. A labeled mask is an image with a limited number of groups. Each groups contains pixels of the same object. Figure 4 shows the proposed deep learning based semantic segmentation model using Unet which is composed of two parts, the training part and the testing part.

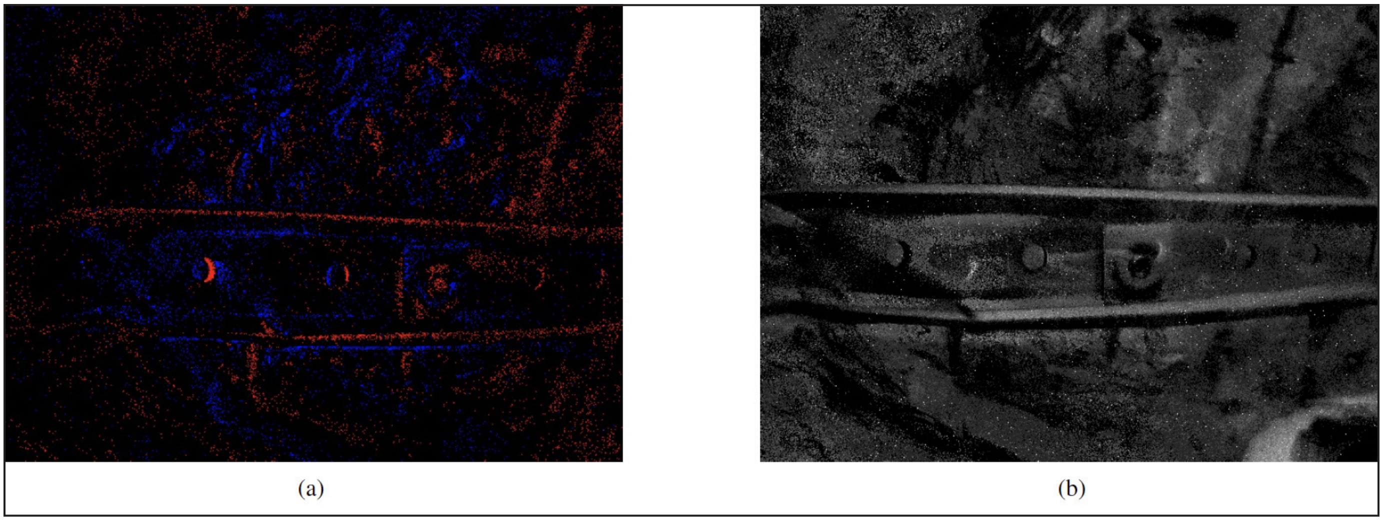


Figure 3. Two types of event camera images: (a) events image. (b) accumulated image

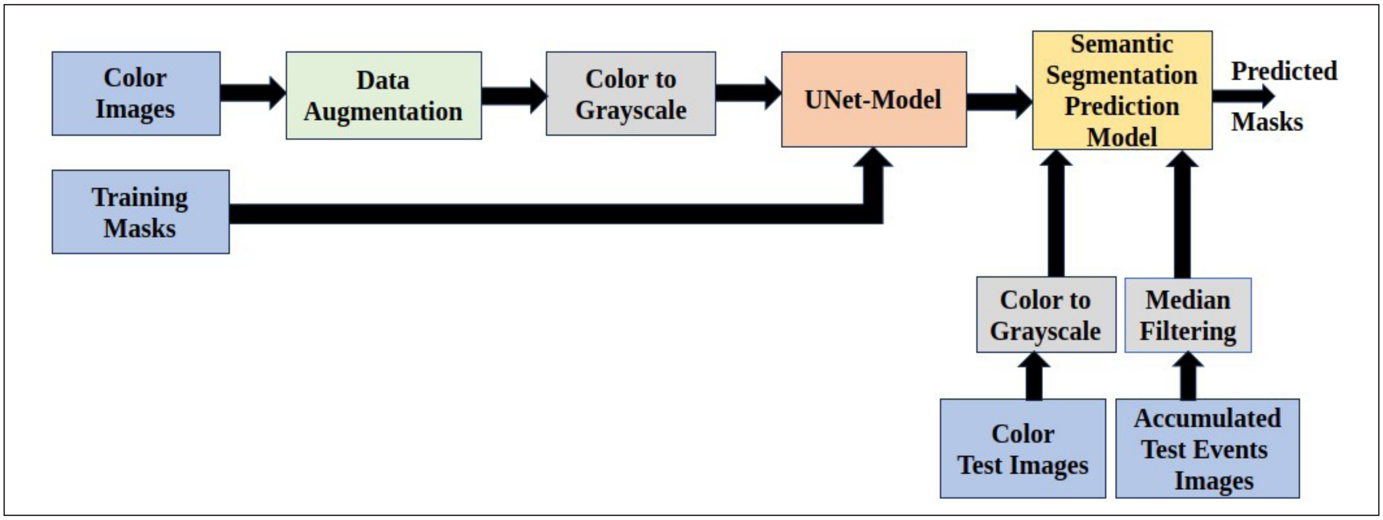


Figure 4. Proposed event based machine learning framework for semantic segmentation. Images from traditional camera are used to train the model while the model can be used to segment images from traditional and event cameras.

A. Training Part

The training part of the proposed framework consists the following main components.

1. *Data Augmentation:* Data augmentation is the process of creating more training images to increase the performance of the deep learning model. In computer vision tasks, data augmentation is implemented using spatial transformation and intensity transformation [29].
2. *Color to gray-scale:* This image processong is used to adapt the deep learning model so that the trained model can be used to predict masks for images that are captured by a regular camera and to predict masks for images that are captured by an event camera.
3. *UNet Model:* The semantic segmentation model is implemented using UNet architecture by [28]. UNet is one of the most popular convolutional neural network used for image segmentation. The architecture of UNet model consists of two main parts: the encoder and the decoder. The encoder is a conventional convolutinal neural network which consists 3×3 convolution layers, linear rectified function, and 2×2 maximum pooling. The encoder down samples the input images at a constant spatial rate with a strides of two at each pooling layer which reduces the computation cost of the model during the training. The decoder up samples the extracted features by 2 × 2 from the encoder part. The output layer is 1 × 1 convolution layer to classify each extracted pixel.

B. Testing Part

The testing part includes the trained semantic segmentation model, the color to gray-scale component, and the median filtering. The color to gray-scale prerocessing is used to predict masks for test images that are captured by regular cameras while the median filtering preprocessing is used to predict masks for accumulated images that are captured by event cameras. The median filtering on the accumulated events images is the key component to adapt the color-based deep learning model to to be used for the segmentation of images from traditional cameras and images from event cameras. The median filtering removes the noise from the accumulated images and preserve the edges.

EXPERIMENT

Data has been collected from Edgar-Mine in Idaho Springs, Co by two types of cameras; an L515 LiDAR-camera by Intel® RealSense™ and two DVXplorer Mini event cameras by Inivation. The sensors setup is as shown in Figure 5. The L515 LiDar-camera produces color images of size 480×680 which are used for training and testing of the proposed semantic segmentation model. The event camera produces accumulated images of the same size as the color camera. The hyper-parameters for the deep learning model are as given in Table 1.

PERFORMANCE EVALUATION METRICS

Since the segmentation task is a pixel level classification, the data to be analyzed to evaluate the performance of the proposed model is represented by four variables which are:

- TP: true positive where a pixel of a class of interest (a rock pixel) is correctly classified as pixel of rock region.
- TN: true negative where a pixel of a non-interest class (a non-rock pixel) is classified correctly.
- FP: false positive where a pixel of a non-interest class is incorrectly classified as pixel of a class of interest. In autonomous roof bolting, a pixel of non-rock region is classified as a pixel of a rock region.
- FN: false negative where a pixel of an interest class is incorrectly classified as a pixel of a non-interest class.

It is desired to increase the true positive and true negative metrics while it is required to reduce the false positive and false negative metrics. The confusion matrix is used to show these four variables.

From these four measurements, four metrics can be calculated to evaluate the performance of a deep learning model which are accuracy, precision, recall, and F1 score which are given by equations 2–5 [30].

Figure 5. Cameras Setup for Collecting Real Data. Two Event Cameras and L515 LiDAR Camera.

Table 1. Deep learning Model Hyper-Parametrs

Model Hyper-Parameters	Value
Image Size	256×256
No. Classes	2
No. Epochs	15
batch_size	16
Learning Rate	10^{-4}
Buffer Size	1,000
Training Data	75%
Validation Data	15%
Testing Data	10%

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{3}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{4}$$

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

Each of these four metrics provides specific insights into the performance of the deep learning model. For example, the accuracy metric shows the correct prediction among all classes. The precision metric indicates the correct prediction of the positive class (rock) and used to minimize the false positive while the recall metric indicate how the machine learning model correctly identifies the true positive from all the actual positive samples and used to minimize the false negative. The F1 score balances between the precision and recall.

RESULTS

A. Model Performance

Figure 6 shows the performance of the deep learning based binary semantic segmentation during the training and validation in terms of loss while Figure 7 shows the performance in therms of accuracy.

B. Model Testing

The model has been tested on color images from a traditional camera and also on accumulated images from an event camera.

DISCUSSION

From the results of the proposed model, the proposed deep learning based semantic segmentation model affords acceptable results for segmenting the input images into two regions (binary segmentation); rock regions and non-rock regions. As it can be seen from Figures 7 and 8, the learning curves are smooth after seven training epochs. The training accuracy and validation accuracy of the proposed model are around 98% at a relatively small epoch 14 as shown in Figure 7 which means non-rock objects.

that the model could learn fast. From Figure 8, the model could provide high performance when it has been tested on new color images. The obtained evaluation metrics are:

- Accuracy =97.36%
- Precision =99.55%
- Recall =93.36%

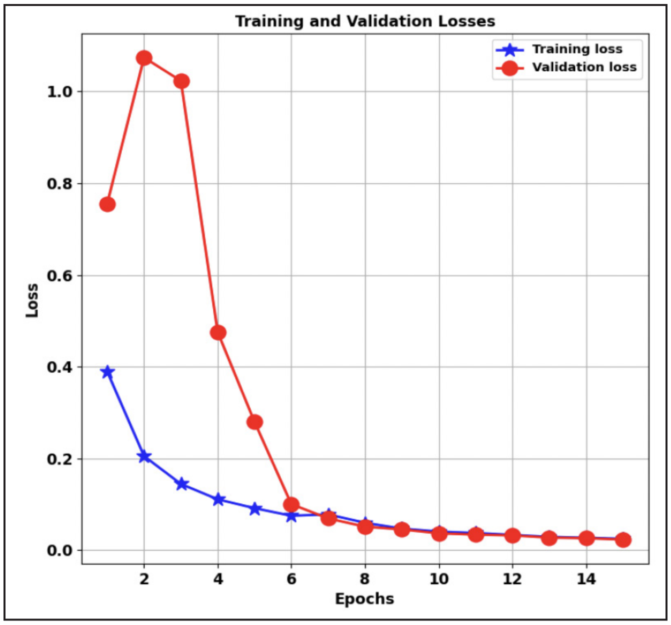


Figure 6. Training and validation learning curves of the losses for the proposed semantic segmentation model. The lossesare decreasing and smooth after seven epochs.

- v1 score =96.36%

Comparing the learning accuracy in Figure 7 with the testing accuracy in Figure 8, the proposed does not suffer from overfitting or under-fitting which means that the proposed model is robust and can be used in different underground mines. The model succeeded to segment color images that have been captured by a traditional camera and classify the pixels that belong to rocks from pixels that belong to straps. In addition, the model could locate the holes in the straps which belong to rock.

Figure 9 shows the testing of the model for the scenario where the scene contains rocks and multiple straps where some of the straps contain holes. As shown in Figure 9, the proposed semantic segmentation model could classify small holes inside the straps as rocks, and this will help also for drilling holes in straps safely. Figure 10 shows the ability of the proposed model to distinguish power cables and straps as non-rock regions. Figure 11 shows testing the proposed deep learning semantic segmentation model on accumulated images collected by an event camera. Even though the deep learning model has not trained on images from event cameras, it could provide acceptable results when it is tested on accumulated event images. As shown in Figure 11, the model could distinguish straps and power cables as non-rock. This means that the proposed model not only applicable for new test images, but it is also applicable for testing images that are different from those that have been used for the training of the model.

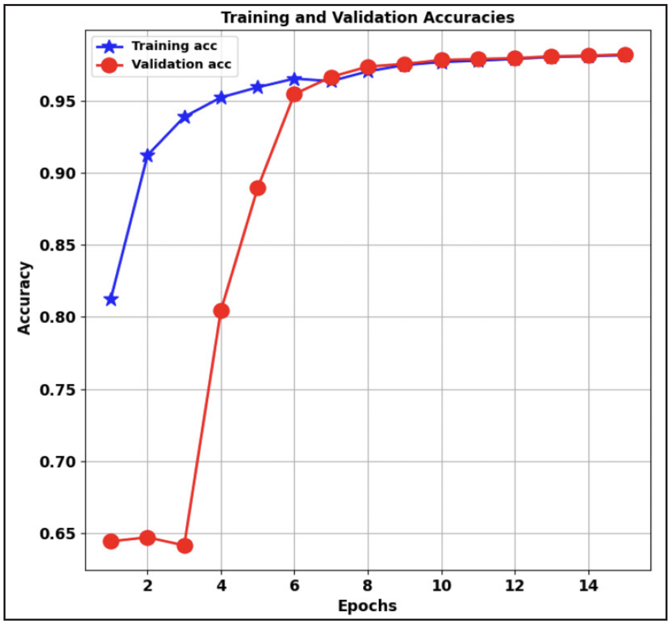


Figure 7. Performance of the proposed deep learning based semantic segmentation model in terms of accuracy during the training and validation

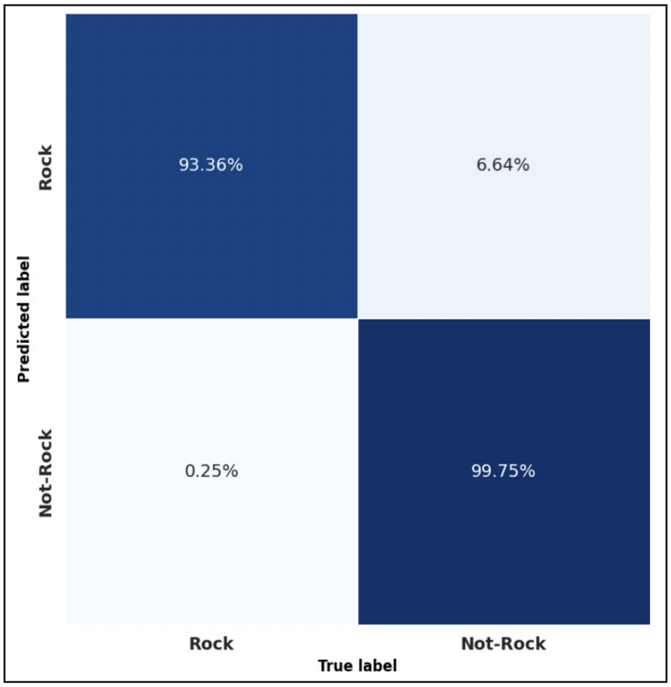
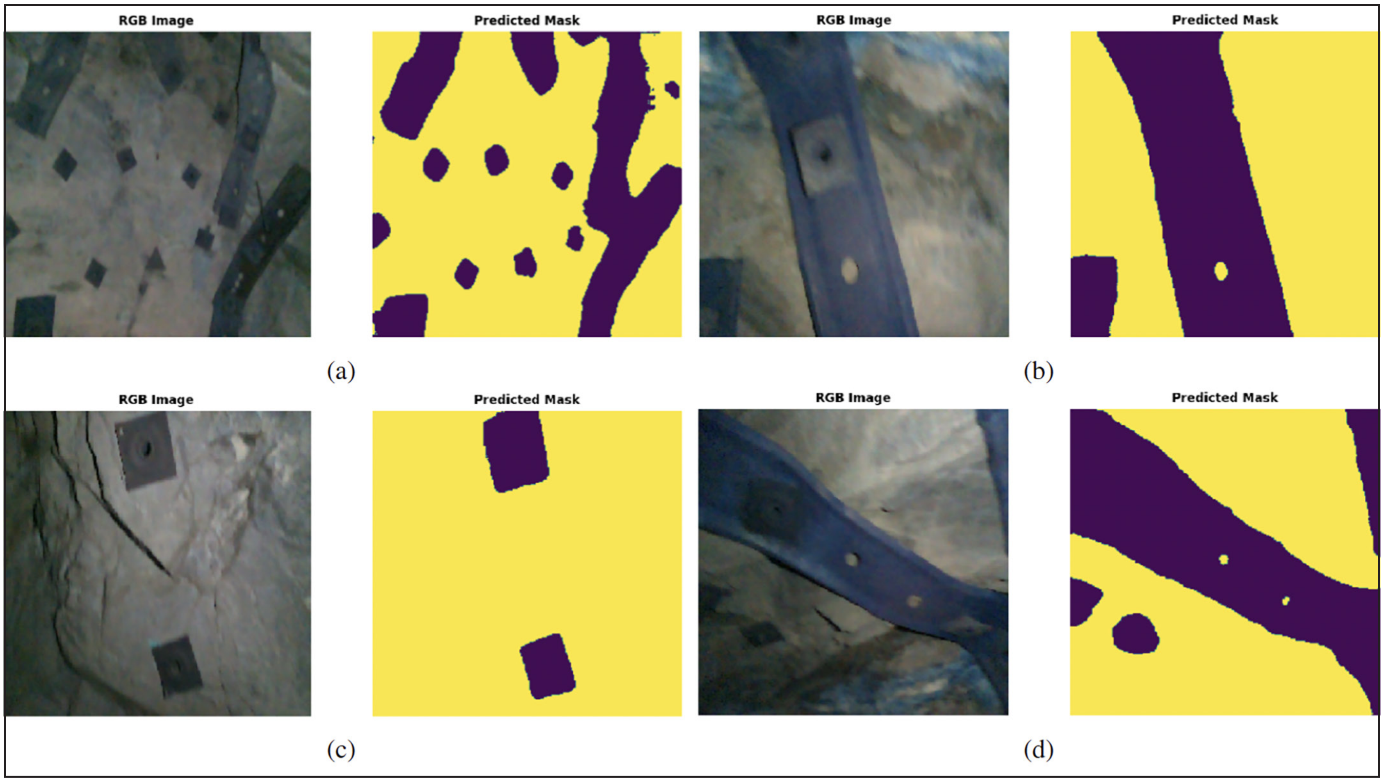


Figure 8. Confusion matrix of the proposed semantic segmentation model tested on unseen color images

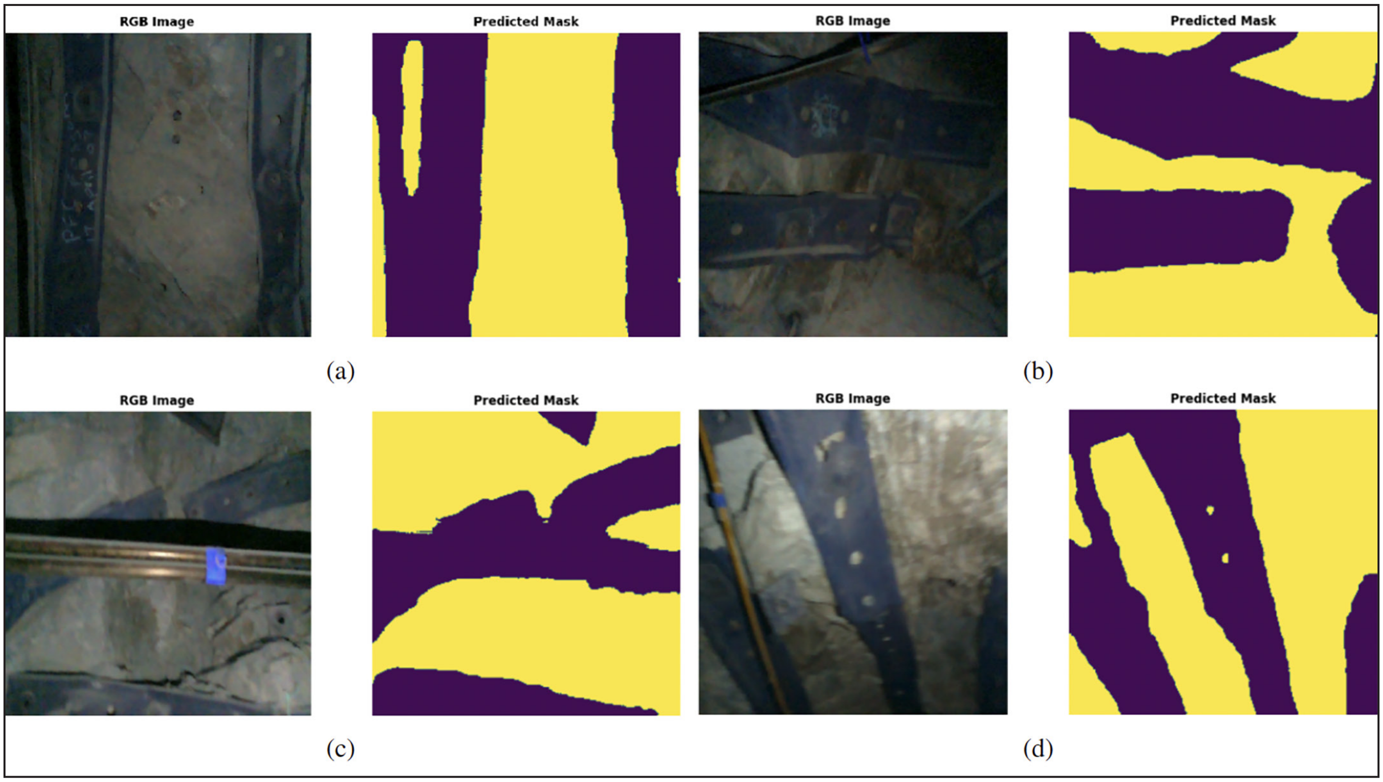
CONCLUSION

In this research, the authors proposed an adaptive deep learning based semantic segmentation model which is necessary to automate roof bolting in underground mine. This research addressed the harsh environment in underground



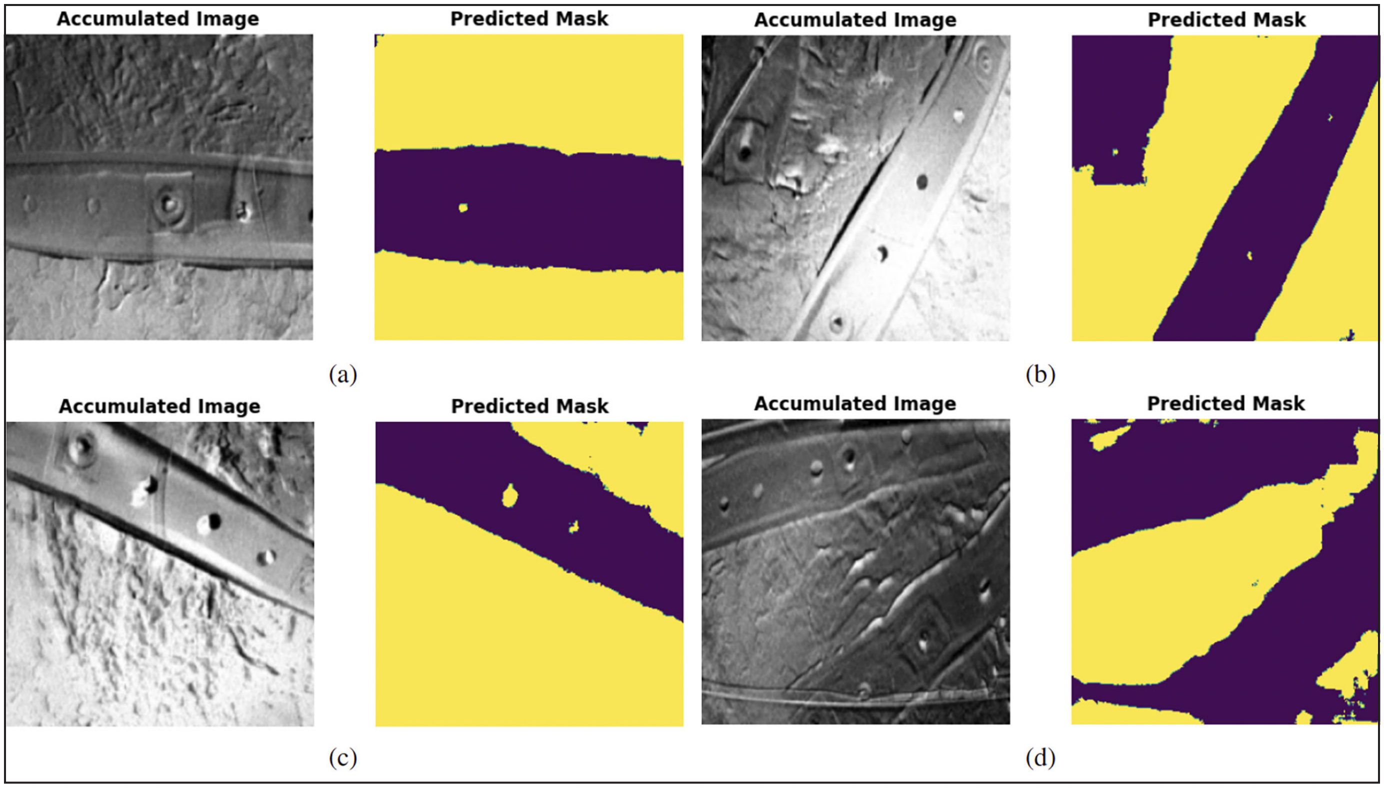
(a) (b) (c) (d)

Figure 9. Binary semantic segmentation of images from color camera into rock and strap regions



(a) (b) (c) (d)

Figure 10. Semantic segmentation of images from color camera into rock and non-rock with the ability to distinguish multiple non-rock objects



(a) (b) (c) (d)

Figure 11. Semantic segmentation of accumulated events images from an event camera. Unseen accumulated images have been segmented to rock and non-rock regions by the proposed deep learning semantic segmentation model.

mine by using a state of are neuromorphic inspired sensors which is known as event camera. The obtained results show that the proposed model could classify the scene in underground mine into regions; rocks and non-rocks. This research represents the base for applying deep learning based semantic segmentation model to digitize mining industry for increasing miners safety.

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24-034

Enhancing Ventilation and Development Planning in Underground Stone Mines: Insights from a CFD-Based Study

Khaled Mohamed
CDC NIOSH, Pittsburgh, PA

Jim Addis
CDC NIOSH, Pittsburgh, PA

Marcia Harris
CDC NIOSH, Pittsburgh, PA

Kumar Vaibhav Raj
CDC NIOSH, Spokane, WA

Vasu Gangrade
CDC NIOSH, Pittsburgh, PA

Snigdha Sarkar
KETIV Technologies, Brea, California

ABSTRACT

The National Institute for Occupational Safety and Health (NIOSH) conducted a ventilation assessment for a recently established underground room-and-pillar stone mine implementing split-mine ventilation. The primary objective was to examine the impact of the length of the in-place stone stoppings on face ventilation efficiency. These stone stoppings serve to separate the intake and exhaust entries and align with the mining direction. To achieve this, computational fluid dynamics (CFD) modeling was utilized. The appropriate turbulence model was selected, and a mesh convergence analysis was conducted for the CFD model. Following that, the CFD model was validated using the conducted ventilation surveys.

Two configurations of in-place stone stoppings, designated as Layout-I and Layout-II, were simulated using the validated CFD models. Layout-I featured a shorter in-place stone stopping, while Layout-II had a longer one. The results obtained from the CFD models demonstrated that the increased length of the in-place stone stopping in Layout-II resulted in a notable enhancement in ventilation efficiency at the advanced faces (last stopping), elevating it from 4% in Layout-I to 8.4% in Layout-II. However, no significant impact of the in-place stopping layouts was observed at other faces. In general, Layout-II exhibited a greater circulation of air at the outby stoppings.

INTRODUCTION

Stone mines produce a wide range of raw material such as basalt, granite, limestone, marble, etc. for the construction industry needed for infrastructure development. As of 2020, there are 4,248 stone mining operations with 110 underground operations in the United States (NMA, 2020).

Underground stone mines come with a unique set of challenges, of which ventilation is often the primary challenge. Ventilation of these mines is challenging because of the large entry sizes leading to low airflow velocities and increased natural ventilation effects (Watkins and Gangrade, 2022). To establish effective ventilation in such mines, it typically necessitates delivering the required air volumes and effective planning and positioning ventilation control equipment, such as auxiliary fans and stoppings (Grau and Krog, 2009).

Throughout the 2000s, NIOSH conducted an extensive research initiative dedicated to investigating ventilation in large-opening mines. This research emphasized a significant ventilation challenge faced by these mines, specifically the effective planning of airflow direction (Grau et al. 2006). Studies assessing the effectiveness of various ventilation stoppings within large-opening stone mines revealed that in-place stone stopping could fulfill the same function as a series of stoppings (Krog et al., 2004). Testing