A Machine Learning-based Microseismic Event Location and Wave Velocity Prediction

Zhansaya Maksut
Nazarbayev University, Astana, Kazakhstan

Rakhat Meiramov
Nazarbayev University, Astana, Kazakhstan

Adnan Yazici
Nazarbayev University, Astana, Kazakhstan

Fidelis Suorineni
Nazarbayev University, Astana, Kazakhstan

ABSTRACT: Human-induced seismicity in underground mining has significant impacts on productivity, safety, and operating costs. Accurate predictors for microseismic event sources are crucial to minimize disasters such as rockbursts. This study develops machine learning algorithms to predict real-time seismic wave velocities in deteriorating underground mines, using data from Nazarbayev University's School of Mining and Geosciences laboratory. Traditional constant velocity models are imprecise, so the study explores several machine learning models. The best-performing model was Gradient Boosted Decision Tree with an MAE of 7.146 m/s. These findings demonstrate that machine learning algorithms can accurately predict seismic wave velocities in underground mining environments.

Keywords: neural network, decision tree, regression, rockbursts, wave velocity.

1 INTRODUCTION

In the mining industry, rockbursts are frequent and can result in accidents, production loss, and financial losses (Feng et al., 2017 and Liu et al., 2019). Microseismic monitoring systems are being developed to mitigate the effects of rockbursts by accurately locating the origin of microseismic events. The seismic monitoring system needs automated processing for event detection, wave arrival time, and event location. A changing mining environment requires a seismic velocity model with an anisotropic heterogeneous geological model for accurate event source prediction.

Deep learning (DL) is increasingly popular for microseismic event source location, due to its ability to identify patterns without manual feature engineering. This paper optimizes machine learning algorithms for wave velocity prediction in a changing environment using linear regression, Deep Neural Networks (DNN), and Gradient Boosted Decision Trees (GBDT). The methodology, machine learning models, results, and findings are discussed in detail in the following sections.

2 DATA EXPLORATION

The technique of learning from data in order to quickly identify which data items are of relevance is known as data exploration. The raw data should be carefully chosen and cleansed in order to ensure credible exploration findings.

2.1 Initial Data

A research team at the Nazarbayev University School of Mining and Geosciences laboratory produced the raw data for this investigation. On a rock cube with blocks that had holes of various diameters, backfilled with various cement/sand ratios, and fractured to mimic various mining conditions, the arrival time of the pulse wave generated by one of the sensors as a source was recorded by the other sensors during data collection. The School of Engineering and Digital Sciences at the same university is where the machine learning application research was conducted.

The enquired data had 3 different divisions: base (839 readings), G80 Narrow-Band sensors cracked (269 readings) and Cracked Cubes SR150M sensors (674 readings) from 8 various sensors (where sensor 1 is the source). Overall, initially there were 1782 readings provided. Each sensor reading had the parameters as follows: location (x, y, z coordinates), distance from source (in mm), velocity, arrival time (in ms), whereas the source had only the location (x, y, z coordinates).

The dataset from these experiments provided us with the coordinates of the source and the receiving sensors, the arrival time at which each of the sensors receives the wave, the quality parameters of the backfill that affect the velocity of the wave, as well as the quality of the fractured and unfractured cubes in the form of the Rock Mass Rating (RMR) system together with their corresponding wave velocities.

For the block description:

- The samples of the blocks were made of concrete or granite
- There were cubes of various sizes with and without holes (in mm): 150, 225, 300, 375, and 450
- Hole diameters in the centre of the cubes varied with cube sizes
- The holes in the cubes were unfilled and filled with cement and sand at different ratios such as 5%, 10%, 15%, 20% cement, dry and wet sand, etc.
- For each of the cement % content in the hole of the cube, the material in the hole was tested at 8 hours, 1 day, 7 days, 14 days, and 28 days
- Each cube size was also fractured (broken up) using a static cracking agent and tested. The fractured cubes were assessed for the block quality using the Rock Mass Rating (RMR) system (Bieniawski, 1989). Hence each fractured block had different quality depending on the degree of fracturing.

Some parameters stored mixed values of qualitative and quantitative data. Some parameters had missing values. There were duplicate parameters, such as the average value of velocities from all sensors for each record separately. There were fields where the values were not applicable.

2.2 Dataset handling techniques

Several methods were employed to process the dataset so that it can be fed into the neural networks. These techniques improved the overall accuracy of the model by ensuring that the data fed into the network was properly pre-processed and free of errors or inconsistencies. This step was critical in achieving the desired results and was a crucial factor in the success of the project.

One-hot encoding: The qualitative data were isolated from the numerical values as independent parameters to standardize the dataset. Each qualitative value then became a separate parameter with a binary value of either 0 or 1 (present or absent). For instance, the cement content parameter included percentages of the cement content as well as varieties of content, such as no hole, no backfill in the hole, dry sand, water-saturated sand, and wet sand, all of which were stored in a single column. As a result, new parameters for the content types (in Boolean data types) were separately established, and the column of cement content was reduced to the original percentages and qualitative data, which were both replaced with 0 in case there was no cement content.

Handling missing values: We have substituted any missing values in the dataset with the mean of the corresponding field. The mean value of all the other applied backfill strength values with the same curing time was used to fill in the missing data, such as when not all records contained information regarding the backfill strength (MPa). For instance, it is preferable to enter the average of known samples of 7-days-cured backfill if a value for the backfill is absent.

Handling recurring parameters: The dataset we were given was extremely detailed, and the School of Mining and Geosciences team made every effort to provide as much information about the experiments as possible. However, from the perspective of machine learning, some details were overlapping, so we sorted or removed some parameters to make the training process steadier. For instance, the raw data featured a unique parameter referred to as "qualitative data" that provided the block description, including the size of the block, the type of backfill, and whether the block had a hole in it. The summary field was eliminated since it was unnecessary because we already have these parameters as separate fields.

After the dataset cleaning, for each channel (sensors, except for the source) the dataset consisted of 23 different parameters and the source sensor consisted of 17 different parameters (we have generated 8 different documents for each sensor separately). The number of readings after the data cleaning for all the sensors was 1365 readings overall.

3 MACHINE LEARNING METHODS

This study improves upon previous research in Maksut et al. (2022) by using various machine learning techniques, including Linear Regression, Neural Networks, and Decision Trees, to predict velocity. The study includes new neural network models and a new Decision Tree approach, as well as individual velocity predictions for 7 sensors to assess accuracy and reliability. The models predict the dependent variable using independent variables and employ different techniques. Due to space restrictions, the study only briefly explains the machine learning models used.

Linear Regression uses a linear model to predict the dependent variable based on independent features. The model aims to minimize the difference between the predicted and actual values. Linear Regression is simple to implement, interpretable, and scalable. It was applied to predict velocity in our research using 22 concrete blocks and wave arrival parameters from 7 different sensors.

Neural networks, also known as Artificial Neural Networks (ANN), simulate the functioning of human neurons by transmitting signals with assigned weights. Deep learning relies on these networks, which can uncover complex correlations and patterns among features. In our research, we built various neural networks with different numbers of hidden layers and neurons per layer, using the rectified linear unit (ReLU) function as the activation function. We tested 12 different neural network configurations with different numbers of hidden layers and neuron amount at each layer.

Decision Trees (DTs), including Random Forest and Gradient Boosted DT, are used in this study due to their prediction accuracy and efficiency. DTs model the decision-making process, but may overfit to the data. Random Forest combines multiple decision trees for collective intelligence but sacrifices interpretability and speed. Gradient Boosted DT builds trees in succession to address shortcomings and minimize loss.

4 DATA ANALYSIS AND FINDINGS

The combined distributions of material condition parameters and velocity indicate that their dependence is non-linear. However, some parameters exhibit a linear relationship in their joint distribution diagrams. For example, there is a strong linear correlation between block size and hole diameter. Additionally, the value ranges for each function are too varied. This diversity can cause instability while training machine learning models, which is addressed by the normalization technique outlined in Section 1.

The variables utilized for training the models are listed in Table 1. It's worth mentioning that the sensor coordinates, distance to source, and arrival time parameters vary based on the sensor (channel), resulting in 7 datasets for each sensor numbered from #2 to #8. The channel #1 is the source channel. However, the other parameters are consistent across all datasets.

Table 1. Variables used in training the models.

Variable		Description
Sample	[-]	The type of the experimental cube (concrete or granite)
Block size	[mm]	The cube side length
RMR	[-]	Rock mass rating, the fractured block quality
Hole	[-]	Boolean value that represents the presence of the hole in the cube
Hole Diameter	[mm]	The diameter of the cylindrical hole in the cube
Cement Content	[%]	Percentage of the cement mixture in the hole
Curing time	[ms]	The time elapsed after the hole was filled
Backfill strength	[MPa]	Backfill material quality
Source coordinates	[m, m, m]	Source coordinates in 3d space
Sensor coordinates	[m, m, m]	Sensor coordinates in 3d space
Arrival time	[ms]	The time at which the sensor captures the wave
Distance to source	[m]	The distance from the sensor to the source

4.1 Results

In this work, we improved upon the study presented in Maksut et al. (2022) by introducing new models for neural network-based algorithms and applying a new Decision Tree approach. Additionally, we decided to predict velocity for each sensor individually to see if it would improve accuracy in comparison with the previous study and identify which sensors may be unreliable. To evaluate the accuracy of the models, we used the Mean Absolute Error (MAE) metric as represented in Equation 1. From each algorithm, the best implementation was selected, and its performance is illustrated in Table 2. In Maksut et al. (2022), the best accuracy achieved was 34.770 m/s, but we were able to improve that accuracy to 7.146 m/s for sensor #2. The accuracy of the models is determined to be high, as the error is found to be distant to the mean of all velocity records, which is 1615.386 m/s.

$$\mathrm{MAE} = \frac{\sum_{i=1}^{D} |x_i - y_i|}{n} \tag{1}$$

Table 2. The testing losses of the best models from each Machine Learning algorithm.

Model		#2	#3	#4	#5	#6	#7	#8
Linear Regression	m/s	618.247	591.091	624.403	478.432	628.081	674.038	673.995
DNN_6_128	m/s	22.017	20.464	29.456	42.989	26.952	27.876	21.394
GBDT	m/s	9.740	7.146	13.500	7.323	7.971	10.251	12.331

Figure 1 demonstrates the effectiveness of the models in predicting unseen data. The graphs compare the actual and predicted values for new records, with the ideal being that they are equal and lie on the line shown on the graph. The closer the points are to the line, the higher the accuracy of the model on the new data. The data in Figure 1 is reinforced by Table 2, which shows that the Gradient Boosted Decision Tree provides the best prediction among all the other models.

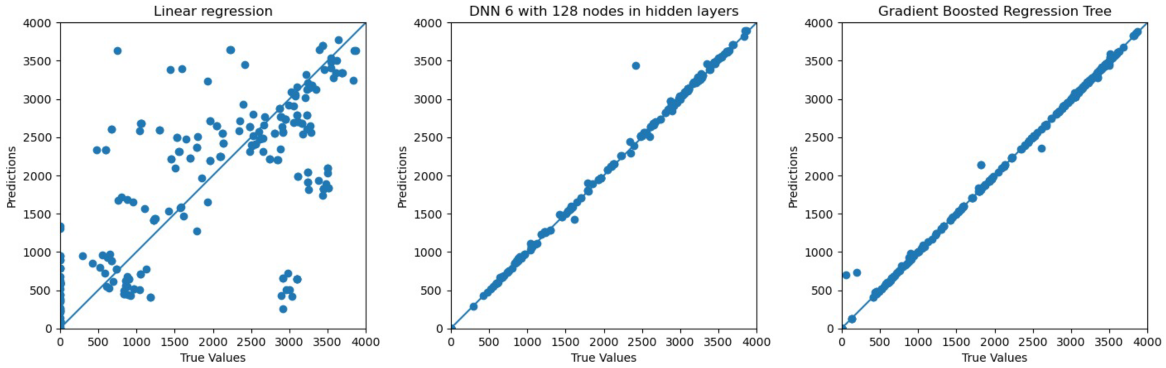

Figure 1. The testing accuracies of the models on the data based on channel #2.

5 SOFTWARE ARCHITECTURE

The Neural Network (Velocity Predictor) takes as input block conditions and sensor data and outputs the predicted wave propagation velocity. This velocity is then passed to the MAE Evaluation, which assesses the accuracy of the velocity prediction using the Mean Absolute Error. Finally, the velocity is used in the Seismic Event Location Calculator to determine the location of the seismic event. The model flow chart is presented in Figure 2.

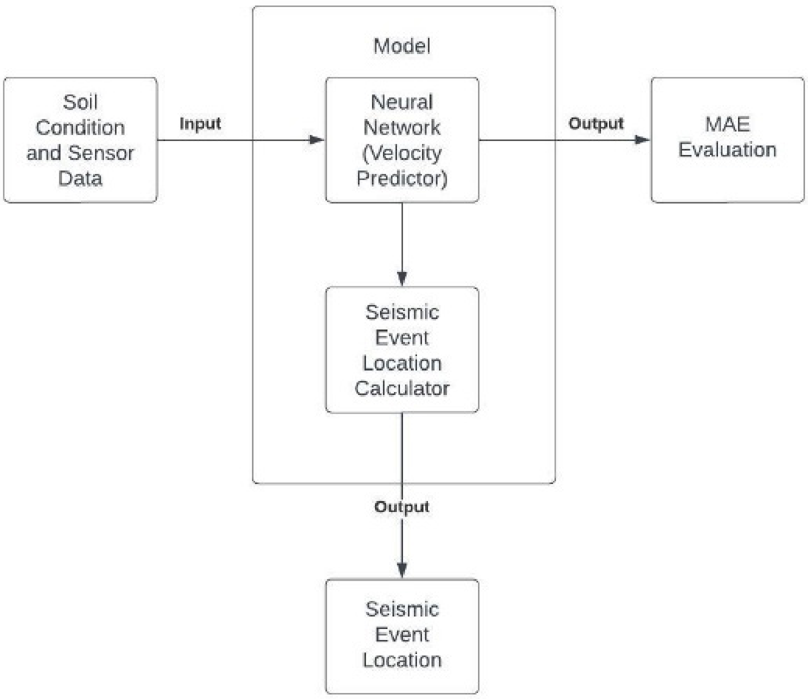

Figure 2. Software architecture for the proposed model.

The neural network architecture for this task consists of an input layer that takes in block condition and sensor data as inputs. These data are then processed through several hidden layers, which use activation functions to transform the inputs into outputs that capture the complex relationships between the inputs and the target wave propagation velocity. The number of hidden layers and the number of neurons in each layer is adjusted to optimize the performance of the model. The final layer of the network is the output layer, which produces the predicted wave propagation velocity.

The MAE measures the average absolute difference between the actual wave propagation velocity and the predicted velocity. The lower the MAE, the more accurate the predictions of the neural network.

6 CONCLUSION

In this research, we aimed to tackle the challenge of predicting the dynamic velocity in a changing mine environment using laboratory data. Our main contribution is the development of an optimized machine learning algorithm for this task. We evaluated various models, including decision trees, and found that the Gradient Boosted Decision Tree model performed best with an error of 9.740 m/s. This small error is important for accurately tracking the velocity in a constantly changing mining environment. However, there is room for further improvement by exploring other non-linear algorithms, decision trees and new data handling techniques. Additionally, other deep learning models such as CNNs and RNNs could be tested in the future.

ACKNOWLEDGEMENTS

This study is supported in part by Nazarbayev University Collaborative Research Program (CRP) under Grant Number OPCRP20200114, with the title of "Real-time Seismic Wave Velocity Determination for Precise Event Source Location in Underground Mines".

REFERENCES

Bieniawski, Z. (1989). Engineering rock mass classifications: A complete manual for engineers and geologists in mining, civil and petroleum engineering

Feng, G. L., Feng, X. T., Chen, B. R., and Xiao, Y. X. (2017). A highly accurate method of locating microseismic events associated with rockburst development processes in tunnels. IEEE Access, 5:27722–27731.

Liu, F., Tang, C., Ma, T., and Tang, L. (2019). Characterizing Rockbursts Along a Structural Plane in a Tunnel of the Hanjiang-to-Weihe River Diversion Project by Microseismic Monitoring. Rock Mechanics and Rock Engineering, 52(6):1835–1856.

Maksut, Z., Meiramov, R., Yazici A., Suorineni, F. (2022). A Machine Learning-Based Microseismic Event Location and Wave Velocity Prediction. 56th U.S. Rock Mechanics/Geomechanics Symposium, Santa Fe, New Mexico, USA, June 2022. doi: https://doi.org/10.56952/ARMA-2022-0166.