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Original Paper

Estimation of Ground Vibration Intensity Induced by Mine Blasting using a State-of-the-Art Hybrid Autoencoder Neural Network and Support Vector Regression Model

Bo Ke,[1,2] Hoang Nguyen ,[3,4,6] Xuan-Nam Bui,[3,4] and Romulus Costache[5]

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In surface mining, blasting is an indispensable method for fragmenting rock masses. Nevertheless, it can inherently induce many side effects like ground vibrations. At high intensities, the ground vibrations generated because of blasting operations can destroy structures and buildings. Also, in areas with adverse geological conditions, such vibrations can cause bench and slope failures. Therefore, the accurate prediction of ground vibration intensity (GVI) has critical implications in mitigating and controlling the adverse effects along with sustainable development and responsible mining. In this research, a novel intelligent model was proposed to predict GVI based on the hybridization of autoencoder neural networks (AutoencoderNN) and support vector machine regression (SVR), and it was named AutoencoderNN-SVR. Nine input variables were utilized to estimate GVI: borehole diameter, bench height, borehole length, burden, spacing, hardness coefficient, powder factor, maximum explosive charged per delay, and monitoring distance. Two hundred ninety-seven blasting events were collected, analyzed, and evaluated to achieve this aim. Also, the traditional SVR model without the support of AutoencoderNN, an empirical equation (i.e., USBM), and a nonlinear model based on gene expression programing were applied in this research and compared with the proposed AutoencoderNN-SVR model in terms of GVI prediction. Then, the models' obtained results were analyzed and computed through statistical indices, such as root mean squared error (RMSE) and coefficient of determination (R^2). The AutoencoderNN-SVR's ensemble model was found to have obtained the highest accuracy and lowest error (i.e., RMSE = 1.232 and R^2 = 0.887) compared to the other models and is an insight in predicting GVI in mine blasting with high reliability.

[1]School of Resources and Environmental Engineering, Wuhan University of Technology, Wuhan 430070, Hubei, China.
[2]School of Intelligent Construction, Wuchang University of Technology, Wuhan 430223, China.
[3]Department of Surface Mining, Mining Faculty, Hanoi University of Mining and Geology, 18 Vien str., Duc Thang ward, Bac Tu Liem district, Hanoi 100000, Vietnam.
[4]Center for Mining, Electro-Mechanical Research, Hanoi University of Mining and Geology, 18 Vien str., Duc Thang ward, Bac Tu Liem district, Hanoi 100000, Vietnam.
[5]Department of Civil Engineering, Transilvania University of Brasov, 5, Turnului Str, 500152 Brasov, Romania.
[6]To whom correspondence should be addressed; e-mail: nguyenhoang@humg.edu.vn

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Highlights

- An autoencoder neural network was investigated to predict GVI in mine blasting;
- An autoencoder neural network was combined with support vector regression to generate a robust hybrid model (AutoencoderNN-SVR) to predict GVI in mine blasting;
- The proposed AutoencoderNN-SVR model was compared with the empirical, SVR, and GEP models;
- The proposed AutoencoderNN-SVR model was introduced as a novel and robust technique for predicting GVI with high accuracy.

KEY WORDS: Ground vibration, Mine blasting, Autoencoder neural network, AutoencoderNN-SVR, Deep learning, Open-pit mine.

INTRODUCTION

Max Planck, a famous physicist, once said, "*Mining is not everything, but without mining, everything is nothing*." Indeed, the mining industry is involved in the production of many raw materials like metals, nonmetals, cement, construction and automobile materials, and cosmetics. These materials are mainly extracted by surface or underground mining. Among these processes, surface mining is a potential method with high production (Ramani, 2012).

To extract minerals (e.g., quarry, coal, ore) through surface mining, open-pit mines often use the drilling-blasting method to remove and fragment rocks or ores with high capacity. This method is effective and compatible with the open-pit mines having high mechanization capacity. However, adverse side effects occur during blasting in open-pit mines, such as over-pressure, flyrock risk, and ground vibration (GV) (Agrawal & Mishra, 2019; Ainalis et al., 2017; Ak et al., 2009; Amiri et al., 2016; Armaghani et al., 2014). Particularly, GV in open-pit mines is a significant concern for engineers and researchers.

To solve this problem, researchers and engineers have applied many techniques, which are divided into two groups: measurement of ground vibration intensity (GVI) and mitigation of GVI using empirical equations and soft computing models (Nguyen, 2020). In the first method, blasting seismographs, such as Blastmate III, Micromate (Instantel–Canada), Mini-Seis, Mini-SuperGraph II, and V901 Seismograph are used. Some blasting

Table 1. Some equations and soft computing models for predicting GVI

Author(s)	Technique	Accuracy
Nguyen et al. (2019c)	USBM empirical	53%
Nguyen et al. (2019c)	Ambraseys empirical	75%
Khandelwal et al. (2010)	SVM (Support vector machine)	95%
Fisne et al. (2011)	FL (fuzzy logic)	91%
Mohamadnejad et al. (2012)	SVM	82%
Monjezi et al. (2013)	ANN (Artificial neural network)	93%
Dindarloo (2015)	GEP (Gene expression programming)	97%
Ghoraba et al. (2016)	ANFIS (Adaptive neuro-fuzzy inference system)	95%
Hasanipanah et al. (2017)	CART (Classification and regression tree)	95%
Abbas and Asheghi (2018)	GFNN (Generalized feed-forward neural network)	95%
Zhang et al. (2019)	PSO-XGBoost (Particle swarm optimization-Extreme gradient boosting machine)	96%
Yu et al. (2020)	HHO-RF (Harris hawks optimization–Random forest)	90%
Bui et al. (2021)	CSO-ANN (Cuckoo search optimization-ANN)	98.7%

seismographs can record and transfer data via the internet or through 3G or 4G cellular communication (Ragam & Nimaje, 2019). Nevertheless, such seismographs can only record GVI once a blasting operation occurs. GVs significantly affect surrounding areas, as they can cause the collapse of buildings, slope instability, and severely affect underground water, benches, and crash structures (Faramarzi et al., 2014; Nateghi et al., 2009; Nguyen et. al., 2020f). However, so far, engineers cannot totally control the GVI of blasting operations.

To control this phenomenon, many researchers have suggested empirical equations and soft computing models for GVI prediction based on the datasets collected by blasting seismographs. Some empirical equations and soft computing models for predicting GVI are summarized in Table 1.

Based on the summarization of the empirical and soft computing techniques in Table 1, the empirical equations often provide lower accuracy than that of soft computing models. However, soft computing models are diverse, and their accuracy is much better than that of the empirical equations. Thus, soft computing models are considered as state-of-the-art algorithms with regard to estimating GVI and controlling its side effects with high reliability, efficiency, and accuracy in open-pit mines (Bui et al., 2019a; Nguyen et al., 2019b, 2019d, 2020e; Nguyen, 2019).

Many intelligent techniques have been proposed to predict the GVs induced by mine blasting, most of which were developed based on standalone machine learning algorithms or through the hybridization of optimization algorithms, as shown in Table 1. The most recent results showed that hybrid models tend to provide better performance compared with standalone models (Amiri et al., 2020; Chen et al., 2019; Nguyen et al., 2020d; Taheri et al., 2017). Yet, autoencoder neural networks (AutoencoderNN) have not yet been applied in predicting GVI in mine blasting. Furthermore, the hybridization of AutoencoderNN and SVR (SVM for regression) has not been considered or developed for this problem. Therefore, in this study, we aimed at investigating the AutoencoderNN's feasibility and combination with the SVR model, named as AutoencoderNN-SVR model, to estimate GVI in mine blasting. Conventional models, such as empirical, SVR, and gene expression programing (GEP), were compared with the proposed AutoencoderNN-SVR model to emphasize its enhancement and performance.

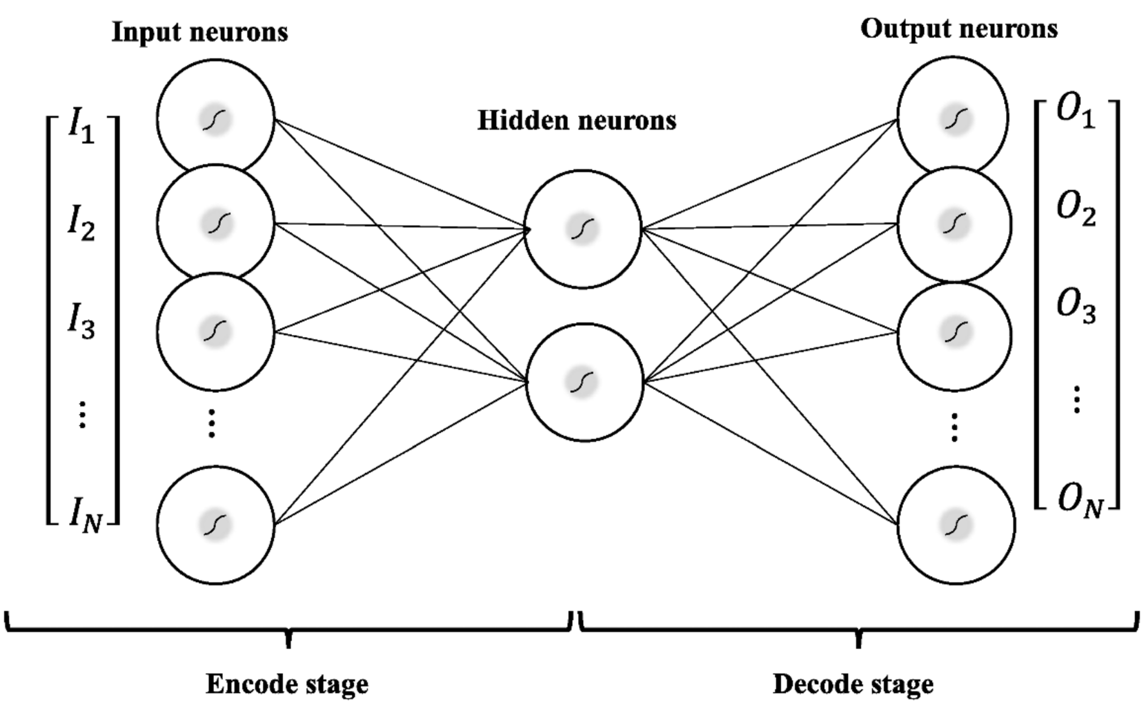

Figure 1. Structure of the autoencoder neural network.

METHODOLOGY

As stated above, this study aimed at developing a novel Autoencoder-SVR model for predicting GVI in mine blasting. To evaluate the quality of the proposed Autoencoder-SVR model, several benchmark models, such as empirical, SVR, and GEP models, were also considered and developed to predict GVI. The empirical, SVR, and GEP models have already been introduced before (Murmu et al., 2018; Azimi et al., 2019; Agrawal & Mishra, 2020; Nguyen et al., 2020c; Qiu et al., 2021; Yang et al., 2020a; Yang et al., 2020b; Bayat et al., 2021; Lawal et al., 2021; Zhou et al., 2021a, 2021b); therefore, we only focused on the development and implementation of the novel Autoencoder-SVR model in this study.

Autoencoder Neural Network

Autoencoder neural network, an unsupervised learning algorithm, is a type of artificial neural network (ANN) that can be used to solve compressed raw data (Diallo et al., 2021). It is also known as a deep-learning algorithm for training ANN models to solve regression and classification problems. Generally, autoencoders use algorithms, mechanisms, and structures similar to the ANN model. However, this network consists of two phases, encoder and decoder, as sub-models (Fig. 1). Whereas the encoder compresses the input variables of a dataset, the decoder recreates the input variables and makes the number of output variables equal to the number of input variables (Fig. 1). The decoder is discarded after training a network, and only the encoder is kept to compress examples to the vector output (Yang, Rad, et al., 2020; Yang, Zhang, et al., 2020). Further details of autoencoders have been previously introduced in the literature (Islam et al., 2021; Laubscher & Rousseau, 2021; Mrabah et al., 2020; Nakano & Takahashi, 2020; Verboven et al., 2020).

Support Vector Regression (SVR)

SVR is the SVM version introduced by Drucker et al. (1997), and it is utilized for regression procedures. This algorithm was improved based on the basic SVM algorithm (for classification problems) introduced by Cortes and Vapnik (1995). Theoretically, the primary aim of SVM is to minimize the structural risk of achieving good generalization capability. SVM transfers original data into a higher dimension of feature space (Guo et al., 2019; Nguyen et al., 2020a) and uses support vectors to calculate outcomes based on the hyperplane and margin. Furthermore, kernel trick is used to build expert knowledge to minimize the complexity of predictive models and prediction errors (Raghavendra & Deka, 2014), as shown in Figure 2a.

To deal with nonlinear regression or complexity regression problems, SVR maps input spaces into higher dimensions in some feature spaces using nonlinear functions. Subsequently, the standard SVM algorithm is applied to reduce the complexity of models and minimize prediction errors. This task is conducted in a hidden layer (hidden nodes), and the weights between nodes are computed using Lagrange multipliers. Finally, the output is computed based on the SVR nonlinear function, according to Eq. 1. The framework of the SVR model is depicted in Figure 2b.

$$y = f(x) = \sum_{k=1}^{n} \overline{\alpha}_n . K(X, X_n) + b \qquad (1)$$

Hybridization of Autoencoder Neural Network and SVR (AutoencoderNN-SVR)

Taking into account the advantages of autoencoder neural networks and SVR algorithms, this study aimed to examine the hybridization capacity of an AutoencoderNN and an SVR model (AutoencoderNN-SVR model) in estimating GVI. Accordingly, the autoencoder model was initiated as the first step to encode the input datasets. Next, the backpropagation procedure was used to train the AutoencoderNN model and compute the AutoencoderNN model weights. The ‘‘adam’’ function was involved in optimizing the autoencoder model. During training of the autoencoder model, the mean squared error (MSE) was used as the autoencoder model’s loss function. Then, the outputs of the autoencoder model were used as inputs for the SVR model development. Kernel trick was applied to the SVR model as introduced in the principle of the SVR model. Finally, the SVR model outputs were used as the predicted GVI values of the AutoencoderNN-SVR model. The framework of the pro-

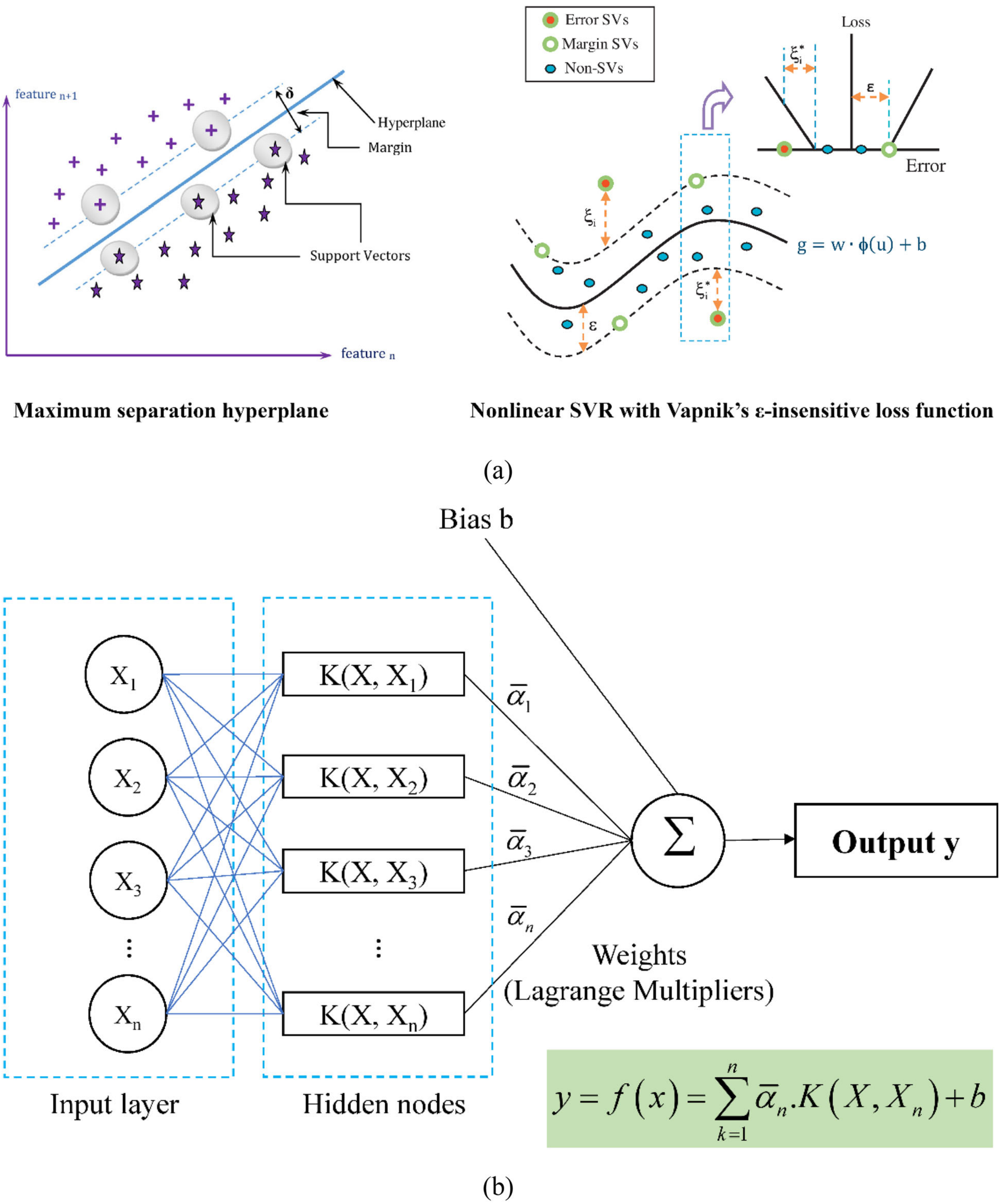

Figure 2. Mechanism and framework of the SVR model. **a** Mechanism of the SVR model; **b** Framework of the SVR model.

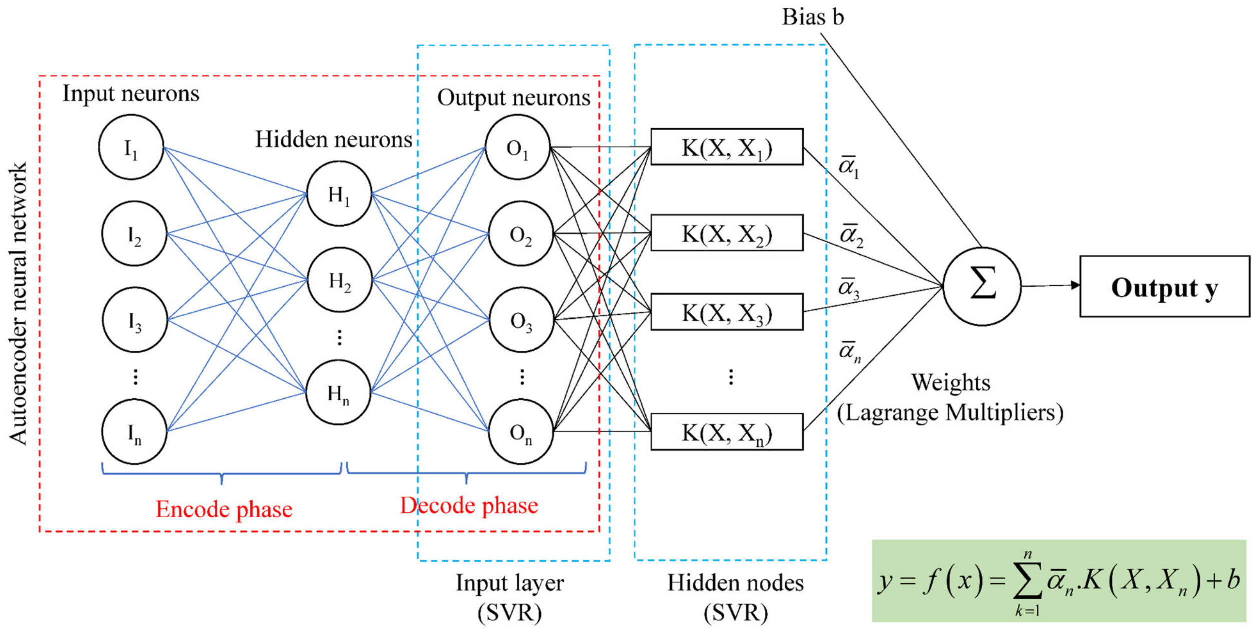

Figure 3. Framework of the AutoencoderNN-SVR model.

posed AutoencoderNN-SVR model is shown in Figure 3.

Dataset used

To investigate the AutoencoderNN model's feasibility in predicting GVI, in this study, we focused on an open-pit coal mine in Vietnam, namely Deo Nai (Fig. 4), across which 297 blasting events were studied. Further details of the study site, as well as its geological conditions, can be found in previous studies (Bui et al., 2019a, 2019b; Nguyen et al., 2018, 2019a, 2020b).

The dataset consists of 297 blasting events along with the borehole diameter (D_k), bench height (H), borehole length (L), burden (W), spacing (b), hardness coefficient (f), powder factor, maximum explosive charged per delay (E), monitoring distance (MD), and GVI. For data collection, the MD values were measured by a GPS receiver. The Micromate device recorded GVI values, and the other parameters were exported from the blasting patterns. Among the used parameters, the first eight parameters were used as input variables to predict GVI. The characteristics of these parameters are visualized in Figure 5.

RESULTS AND DISCUSSION

To develop the AutoencoderNN-SVR model, the proposed framework in Figure 3 was applied. Before applying this framework, a dataset composed of 297 blasting events was preprocessed. The dataset was normalized using the MinMax scaling method in [0, 1]. Then, it was divided into two sections: 70% as the training samples and 30% as the testing samples. The testing stage aimed at checking and verifying the performance of the developed AutoencoderNN-SVR model based on the training dataset. This stage was considered as an experimental testing step since the testing datasets were unseen and not used to train the AutoencoderNN-SVR model.

Once the dataset was well prepared, the training sample was involved in the AutoencoderNN-SVR model development. When defining and compiling the AutoencoderNN-SVR model, the "ReLU" function was used as the active function, the "adam" function was used as the optimizer, and MSE was used as the loss function. To implement the AutoencoderNN model, a network topology with three layers was established, where the input layer contained 8 neurons, the hidden layer contained 16 neurons, and the output layer contained 8 neurons. The AutoencoderNN model was implemented with 1000 epochs. The performance of the

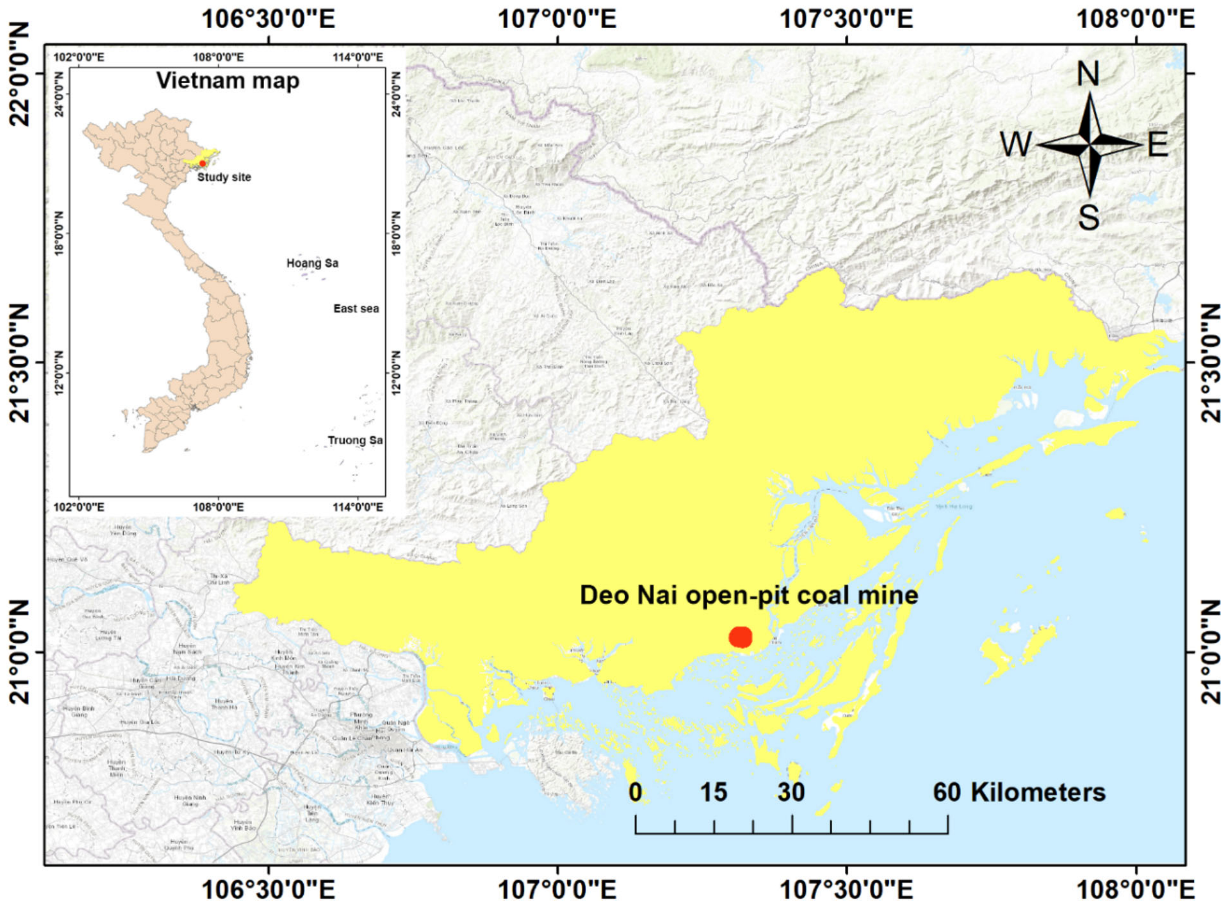

Figure 4. Location of the study site.

autoencoder model during training is highlighted in Figure 6.

The training autoencoder model's learning curves showed that the model achieved an excellent fit and that it well reconstructed the inputs. Alternately, the model was steady throughout the training, and overfitting did not occur. Therefore, the reconstructed inputs were used as new inputs for the SVR model to predict GVI in the next step. Finally, the hybrid Autoencoder NN-SVR model was defined, and its performance was highlighted, as shown in Table 2.

To evaluate the performance of the AutoencoderNN-SVR model, coefficient of determination (R^2) and root mean squared error (RMSE) were computed. Also, a traditional SVR model without the hybridization of the autoencoder neural network model, an empirical equation (USBM), and a nonlinear model based on the GEP method were compared with the proposed AutoencoderNN-SVR model to evaluate its efficiency compared with that of other models. The equations of the USBM and GEP models are described in Eqs. 2 and 3.

(i) USBM equation:

$$\mathrm{PPV} = 35.249\left(\frac{\mathrm{MD}}{\sqrt{E}}\right)^{-0.384} \tag{2}$$

(ii) GEP nonlinear model: Prior to developing the GEP model, the main GEP settings were established using the following parameters:

- Number of chromosomes: 30
- Head size: 10
- Number of genes: 3
- Linking function: Addition
- Fitness function: RMSE
- Strategy: Optimal evolution
- Lower and upper bounds: [– 10,10].

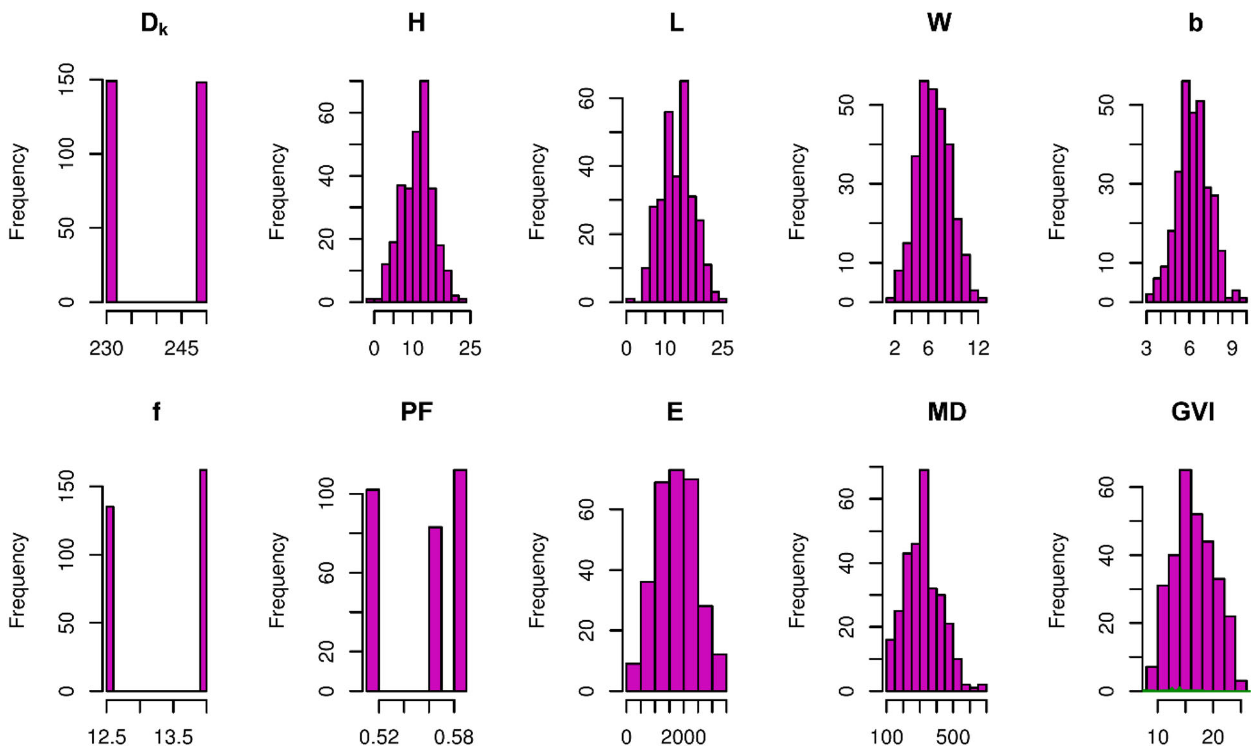

Figure 5. The blasting datasets used in this work.

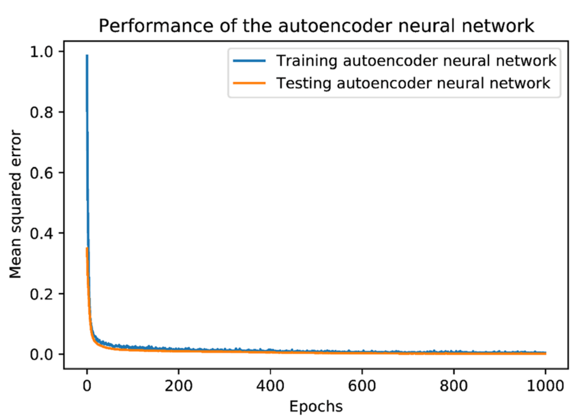

Figure 6. Performance of the autoencoder model in the reconstruction of the inputs.

$$PPV = \sqrt[3]{f} - 63.076\frac{f}{MD} + 707.605 + \tanh\left(\tanh\left(W - f - D_k + MD + 6.747\times\left(\frac{1}{MD} - 3.617\right)\right)\right) + \sqrt[3]{E - ((f + L)\times\tanh(f))} \tag{3}$$

Table 2. RMSE and R^2 of the applied models

Model	Training		Testing	
	RMSE	R^2	RMSE	R^2
SVR	1.048	0.922	1.262	0.879
Auto encoder NN–SVR	1.037	0.925	1.232	0.887
USBM	2.021	0.706	1.843	0.749
GEP	1.745	0.782	1.732	0.787

Once the models were well-developed, their performance was computed and then demonstrated, as shown in Table 2.

In light of the values in Table 2, the USBM empirical model clearly achieved the most deficient performance with the highest RMSE and lowest R^2 in both the training and testing phases. This is because only the E and MD variables are used for the linear equation and USBM model. Thus, the USBM empirical model with a linear function is not suitable for predicting GVI. Whereas, the GEP model

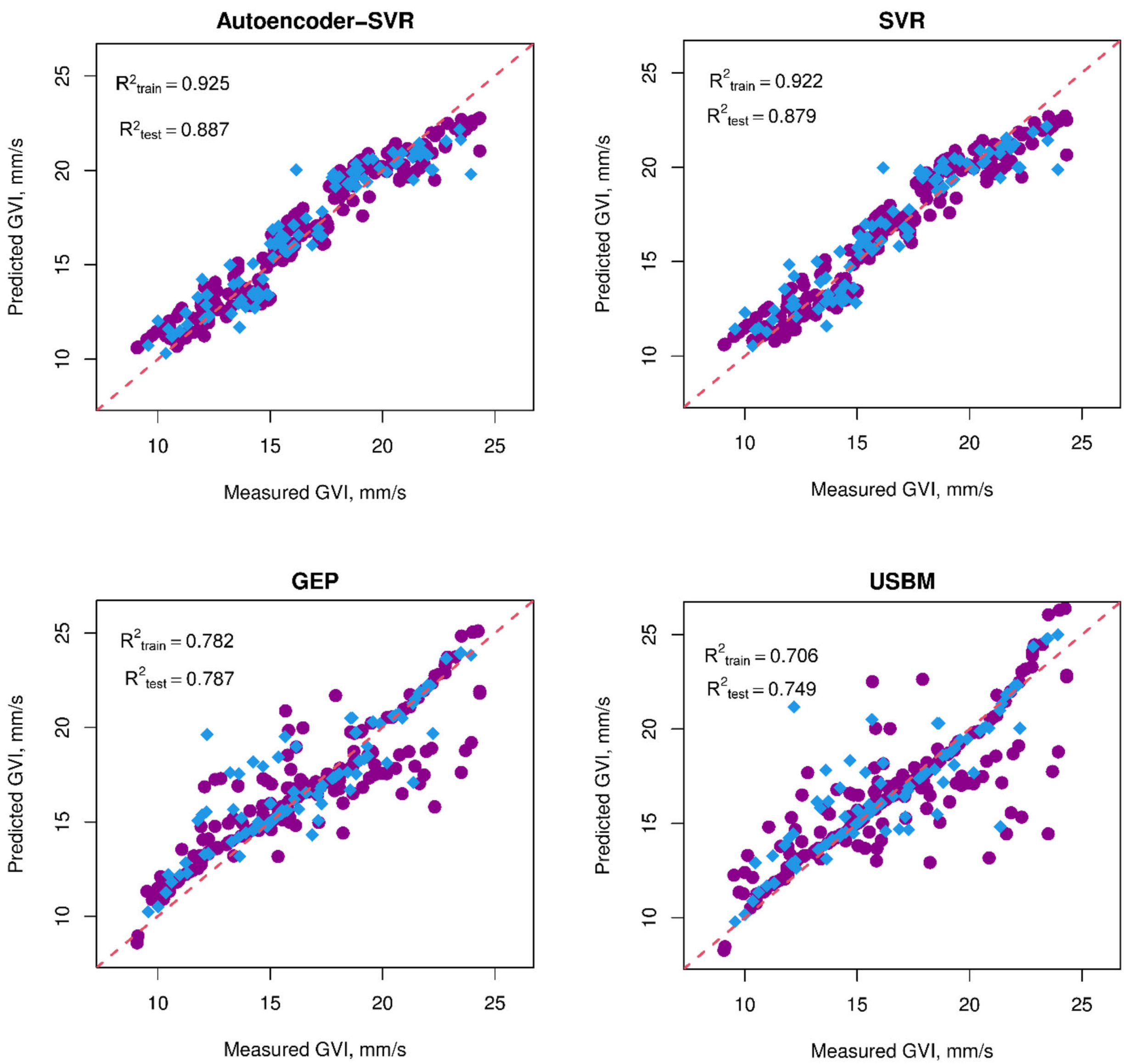

Figure 7. Regression capacity and accuracy of the developed models.

with a nonlinear complexity function provided better performance than the USBM linear regression model. Thus, GVI prediction matches nonlinear models. Therefore, the SVR and AutoencoderNN-SVR models are potential solutions for dealing with this case.

From the comparison of the SVR model with the USBM and GEP models, the SVM performance is observed to be higher than that of the USBM and GEP models. The SVR model's error was significantly reduced, and the R^2 value indicates that this model pretty much fits the used dataset in this study. Owing to the nonlinearity of the used dataset, the proposed AutoencoderNN-SVR model seems to be the best fit model in this study due to the role of the AutoencoderNN model in encoding the inputs. Thus, the autoencoder model can be assumed to have provided a robust solution in encoding the inputs to increase the accuracy of the SVR model in predicting GVI. The details of the measured and predicted GVI values in practice are shown in Figure 7.

We could observe the convergence capacity of the models as well as how far the predicted values

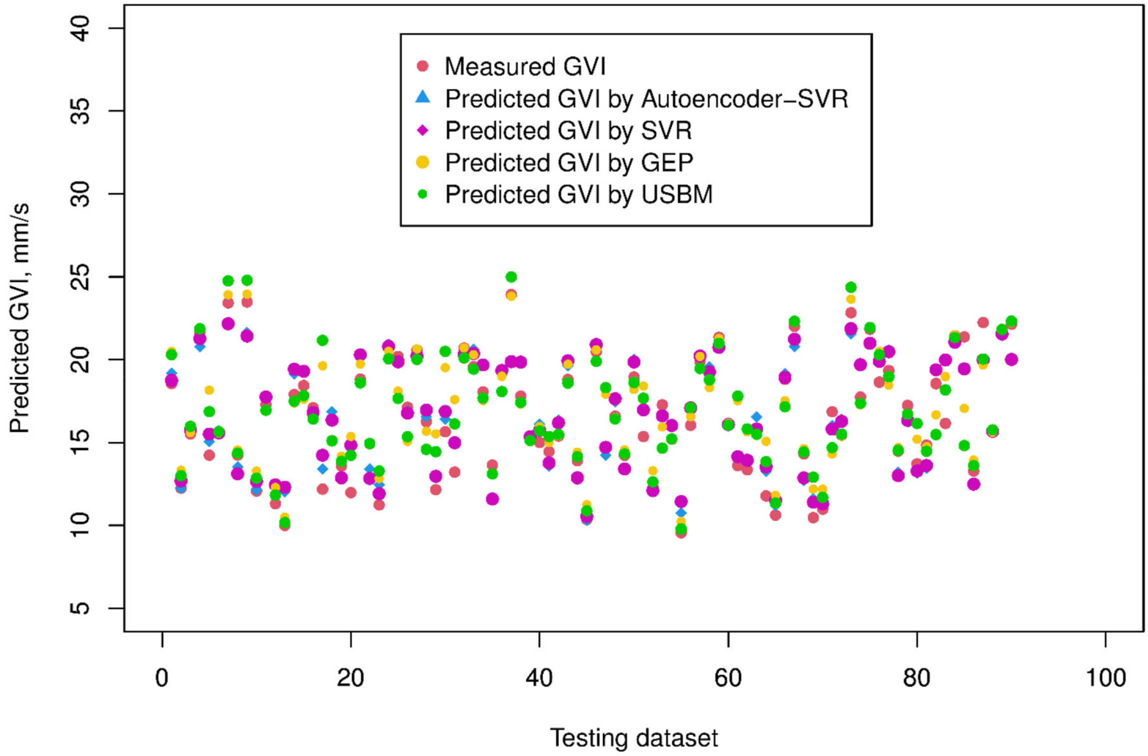

Figure 8. Differences between among GVIs predicted by the individual models.

matched practical engineering data. The performance of the proposed AutoencoderNN-SVR model was only slightly higher than that of the SVR model; however, this is still significant in the field of geotechnical engineering. Due to the uncertain properties of geological and geographical conditions, improving predictive models in this field are challenging (Hao et al., 2018). Figure 8 shows the improvement of the models in predicting GVI based on different techniques, i.e., linear, nonlinear, encoding, and decoding.

CONCLUSION

The GVs induced by mine blasting in open-pit mines are a major concern for researchers. Although there have been significant efforts made by researchers to predict, control, and mitigate GVI, it is still a challenging topic in the mining industry, especially in open-pit mines. Several previously proposed robust models might be inefficient in various open-pit mines/locations due to the uncertainty in geological and geophysical conditions. Therefore, more insights into various soft computing models would contribute to the current state of knowledge in this particular subject. In this study, a novel soft computing model was proposed, namely Autoencoder NN-SVR, for predicting GVI in mine blasting with better accuracy than that of the currently used models. For the first time, the autoencoder neural network was used in this field and was combined with the SVR model to predict GVI in mine blasting with high reliability. The comparison results showed that the autoencoder neural network played an essential role in improving the SVR model's accuracy in predicting GVI. Remarkably, the empirical method (i.e., USBM) provided poor performance, and it should be further improved in future studies. The nonlinear GEP model provided better performance than the USBM model, but its structure is complex, and the GEP's performance was lower than that of the proposed Autoencoder NN-SVR model. In conclusion, the Autoencoder NN-SVR model is a robust soft computing model and should be used to predict, control, and mitigate GVI in practical engineering.

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