Blast-Induced Ground Vibration Prediction and Uncertainty Quantification in Granite Quarries Using Deep Ensembles Model

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Research Article

Keywords: blast-induced ground vibration, deep neural network, deep ensembles, uncertainty quantification

Posted Date: March 18th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1453558/v1

Abstract

Ground vibration is one of the most dangerous environmental problems associated with blasting operations in mining. Therefore, accurate prediction and controlling the blast-induced ground vibration are imperative for environmental protection and sustainable development. The empirical approaches give inaccurate results as obvious in the literature, hence, numerous researchers have started to use the fast-growing soft computing approaches with satisfying prediction performance. However, not only achieving the high-prediction performance but also detecting prediction uncertainty is very important for especially blasting operations which is a safety-critical system. This study aims to propose the deep ensembles model to predict the blast-induced ground vibration and quantify the prediction uncertainty, which is usually not addressed. The deep ensembles model includes training an ensemble of deep neural networks (DNN) on the same data, by initializing each network randomly, to yield multiple predictions on both the predicted value and the uncertainty value. In this study, 200 published data from ten granite quarry sites in Ibadan and Abeokuta areas, Nigeria were used. The input parameters were the distance from the blasting face and the weight of the charge per delay, while the targeted output was the peak particle velocity (PPV). For comparison, a single DNN model and an empirical equation (USBM equation) were applied. According to the coefficient of determinationR^2, root mean squared error (RMSE), negative log-likelihood (NLL), mean prediction interval width (MPIW), and prediction interval coverage probability (PICP), the deep ensembles model gave both the most accurate predictions and the most reliable predictive uncertainty quantification.

Introduction

Blasting operation is one of the most extensively used techniques to fragment the hard rock in mining and construction activities. Although the advantages of blasting for optimum rock breakage, it generates many adverse side effects, such as dust, gases, air overpressure, fly rock, and ground vibration (Bui et al. 2021; Murlidhar et al. 2020; Ak et al. 2009). Various research studies on blasting operations have revealed that ground vibration is the most destructive result of blasting because it can damage neighboring buildings, roads, the ecology of the surrounding area, and groundwater (Armaghani et al. 2015; Dindarloo 2015; Khandelwal et al. 2017). From a mining production perspective, ground vibrations may damage the stability of benches and slopes and may generate a number of back breaks in open-pit mines (Haghnejad et al. 2018). The ground vibration is unavoidable but it can be reduced to a permissible level. The accurate prediction of the ground vibration is, therefore, crucial to reducing the adverse effects of the blasting operations as much as possible.

The ground vibration is generally recorded based on two factors: PPV and frequency. PPV is considered as the principal parameter to measure the ground vibration and is generally determined using the distance from blasting face (D) as well as the weight of the charge per delay (W) (Singh and Singh 2005a). A number of empirical equations have been proposed to predict blast-induced PPV (Duvall and Fogelson 1962; Ambraseys and Hendron 1968; Langefors and Kihlstrom 1978; Ghosh and Daemen 1983; Roy 1991; Ak and Konuk 2008; Simangunsong and Wahyudi 2015). Nevertheless, according to the

literature, these equations suffer from poor accuracy as they are often site-specific and could not represent all other regions (Iphar et al. 2008; Mohamadnejad et al. 2012; Monjezi et al. 2011; Uyar and Aksoy 2019). To address the shortcomings of empirical equations, nowadays, numerous soft computing (SC) methods have been developed and applied extensively to predict the blast-induced PPV with promising results. Some of the important researches on blast-induced PPV prediction using SC methods are summarized in Table 1.

Table 1
The most important studies on the PPV prediction using SC methods

SC method	Study	SC method	Study
	Singh and Singh (2005b)	FIS	Fişne et al. (2011)
	Monjezi et al. (2011)		Ghasemi et al. (2013)
ANN	Khandelwal et al. (2011)	GA	Kumar et al. (2014)
	Saadat et al. (2014)	GEP	Faradonbeh et al. (2016)
			Monjezi et al. (2016)
Hybrid ANN	Hajihassani et al. (2015)	Hybrid kNN	Bui et al. (2019)
	Amiri et al. (2016)	PSO	Hasanipanah et al. (2017b)
	Azimi et al. (2019)	RF	Yu et al. (2020)
	Taheri et al. (2017)		Zhou et al. (2020)
	Shang et al. (2020)		H. Zhang et al. (2020)
	Bayat et al. (2020)	SVM Based	Khandelwal et al. (2010)
	Nguyen et al. (2020)		Mohamadnejad et al. (2012)
	Huang et al. (2020)		Hasanipanah et al. (2015)
	Bui et al. (2021)		Dindarloo (2015)
ANFIS Based	Iphar et al. (2008)		Sheykhi et al. (2018)
	Armaghani et al. (2015)		Chen et al. (2021)
	Ghoraba et al. (2016)		
	Shahnazar et al. (2017)	XGBoost	Ding et al. (2020)
	Yang et al. (2020)		X. Zhang et al. (2020)
	Xue (2019)		Nguyen et al. (2019)
CART	Hasanipanah et al. (2017a)		

Artificial neural network (ANN); Adaptive neuro-fuzzy inference system (ANFIS); classification and regression trees (CART); fuzzy inference system (FIS); gene expression programming (GEP); genetic algorithm (GA); k-nearest neighbors (kNN); particle swarm optimization (PSO); random forest (RF); support vector machine (SVM); eXtreme Gradient Boosting (XGBoost)

The review of the literature showed that ANN-based models have been the most commonly used to predict blast-induced PPV because of their impressive prediction performance. On the other hand, the use of deep learning, which is gaining much popularity due to its supremacy in terms of accuracy in recent

years, to predict blast-induced PPV is relatively new. For example, Nguyen et al. (2021) have developed a deep neural network (DNN) and used whale, Harris hawks, and particle swarm algorithms to optimize it. Results showed that the optimized DNN predicts blast-induced PPV with outstanding accuracy. However, all of these ANN and deep learning models have generally focused on point prediction (single predictive values given some input data) without any indication of the uncertainty (i.e. risk or confidence) of that prediction. In other words, these models do not capture how much the model is confident in its prediction. Evaluating the efficacy and reliability of any artificial intelligence (AI) models, before they could be implemented in practice is important because the predictions obtained from such models are subject to model inference errors and noise. Deep learning models are also considered as black-boxes and mostly make overconfident predictions (Abdar et al. 2021; Dorjsembe et al. 2021; Gawlikowski et al. 2021). This is an unacceptable feature in risk-sensitive tasks such as blasting in mining operations. Therefore, the prediction uncertainty should be incorporated into the deterministic approximation generated by deep learning models to advance the reliability and credibility of the predictions.

Assessing the quality of predictive uncertainties is difficult as *ground truth* uncertainty is often not available. A variety of approaches have been proposed for understanding and quantifying uncertainty in a DNN's prediction. Monte-Carlo (MC) dropout (Gal and Ghahramani 2016) and ensemble methods are the most widely-used types of uncertainty quantification in the literature (Gawlikowski et al. 2021). MC-dropout is a type of Bayesian approach and makes use of the dropout method to quantify predictive uncertainty. Originally, dropout is used as a regularization method at training time to solve overfitting problems. MC-Dropout uses it both at training and test time to provide randomness to the prediction process. The data is passed through the network multiple times, with different subsets of parameters being dropped randomly at each run. In the end, the outputs (i.e., a set of predictions) are averaged over the run to yield a predictive distribution in the target domain. While the MC-Dropout is a simple method, it is slow and requires more time and memory when integrated into a deep architecture (Abdar et al. 2021).

The deep ensembles model, on the other hand, trains a number of different DNNs with randomly initialized parameters (i.e. weights and biases), adds adversarial training, and then combines the predictions from each network to obtain ensemble mean and variance (interpreted as uncertainty). Candidate networks have very different weight values from one another, and, as a result, they lead to diverse predictions, which yield more accurate predictive distribution. This model has an important potential to make great uncertainty predictions while improving accuracy. Moreover, it is presented as well-calibrated and well generalized in both in-distribution data (i.e. samples seen during training) and out-of-distribution data (i.e. new samples unseen during training) (Dorjsembe et al. 2021). Thus, it would not be site-specific and could be used for approximating blast-induced PPV in each region with high accuracy. Moreover, the deep ensembles model is computationally more efficient than Bayesian-based approaches and tends to perform better in quantifying uncertainty in a variety of tasks in regression and classification (Lang et al. 2022).

According to the best review of the authors, uncertainty quantification with any SC method has not yet been applied to predict the blast-induced PPV. In addition, the effectiveness of DNNs, achieving state-of-

the-art performance on a wide variety of tasks, still needs to be verified in predicting blast-induced PPV. Furthermore, the development of an AI model with high accuracy in different sites, where the effects of blast-induced PPV are dissimilar in each region, is essential for contributing to practical engineering. Therefore, this study proposed the deep ensembles model (Lakshminarayanan et al. 2017), which is often referenced as a base work on uncertainty predictions, to predict the blast-induced PPV values independent of the region as well as to quantify the prediction uncertainty, and thus reduce severe damages of blasting to surroundings. Ten quarry sites from the research literature (Nigeria) were selected as a case study. The rest of the paper is structured as follows: Section 2 provides comprehensive information on the dataset; Section 3 demonstrates an overview of the deep neural network, the uncertainty framework, and deep ensembles models; the blast-induced PPV prediction models are given in Section 4; Section 5 proposes the results and discusses them. Finally, the conclusions are given in Section 6.

Description Of The Data Used

In this study, ten measured blast-induced PPV datasets from ten quarry sites in Ibadan (Offa quarry site, 7.38°N, 3.95°E; Ladson quarry site, 7.37°N,3.97°E; Wetipp quarry site, 7.35°N, 3.87°E; Ratcon quarry site, 7.33°N,3.87°E and Seedvest quarry site, 7.32°N, 3.92°E) and Abeokuta areas (United quarry site, 7.06°N, 3.33°E; Associated quarry site, 7.05°N,3.33°E; Equation quarry site, 7.08°N,3.67°E; Verytaces quarry site, 7.15°N, 3.74°E and Phoenix quarry site, 7.18°N,3.73°E), Nigeria provided by Hammed et al. (2018) were used. The quarry sites are shown in Fig. 1.

These datasets were recorded during the survey of residential buildings in the neighborhood of the quarry sites. Each dataset involved twenty data and comprises PPV, D, and W values. PPV values were measured using the V9000 Seismograph situated at building monitored station points in the dwelling areas surrounding each site. D values in datasets were recorded using a global positioning service (GPS). The ammonium nitrate fuel oil (ANFO) was used as the main explosive coupled with the Magnadet detonator for blasting operations at the defined areas. Table 2 gives a summary of the adopted data with their ranges. Moreover, the matrix analysis diagram of the input and output variables is shown in Fig. 2.

Table 2
Characteristic of the data used

	D	W	PPV
Min	300	650	8
1st Qu	537.5	1250	28.145
Median	775	1500	46.94
Mean	775	1517.64	64.173
3rd Qu	1012.5	1800	83.89
Max	1250	2950	247.53

In Fig. 2, the correlation coefficient between the input variables themselves and between the input and output variables are demonstrated. While there is a meaningful nonlinear relationship between D and PPV, other variables do have not any relationship.

Theoretical Background Of Methods Used

Deep Neural Network

ANN attempts to mirror the neural system of a human brain, where neurons are connected to each other in a complicated network (Trippi and Turban 1992). In an ANN, parameters given to the system as input are processed in neurons. The inputs are multiplied by the randomly selected weight coefficients in the first stage, and their sum is computed with a summation function Σ. Then, a constant value (bias) is added to the neuron and an activation function is applied. An activation function manages the threshold at which the neuron is activated and the strength of the output signal. Generally, differentiable nonlinear activation functions such as sigmoid and hyperbolic tangent are chosen. The bias term here is used to increase or decrease the input of the activation function and is again chosen randomly in the first stage. The value obtained from the activation function is considered as the output node (Cheng and Titterington 1994). A neuron as a computational unit is described by:

$$Z = f\left(\sum_{i=1}^{K} w_i x^i + b\right) \tag{1}$$

where x^i is input features, w_i is weight, b is the bias, $f(.)$ is the activation function and Z is the output.

Multi-layer perceptron (MLP) is considered the best type of neural network and comprises an input layer, hidden layer or layers, and an output layer. The neurons in the MLP are trained with the backpropagation

algorithm that solves nonlinear problems effectively (Haykin 2009). The MLP forms the basis of the deep learning that was developed to improve the model performance of the ANNs. An MLP with multiple layers and deep learning techniques is denoted as a DNN (Nguyen et al. 2021). Fig. 3 shows an example diagram of a DNN consisting of one input layer with 2 inputs, 2 hidden layers with 5 neurons in each, and one output layer with 1 output.

A general simple formula of a DNN to compute predictions based on learned weights and inputs for is described by:

$$f^{out}\left\{\sum_{h_2=1}^{H_2} w_{h_2,m}^{(out)} f^{h_2}\left[\sum_{h_1=1}^{H_1} w_{h_2,h_1}^{(2)} f^{h_1}\left(\sum_{k=1}^{K} w_{k,h_1}^{(1)} x_k + b_k\right) + b_{h_1}\right] + b_{h_2}\right\} \quad (2)$$

where $w_{h_a,h_b}^{(H)}$ is the weight of the link from the neuron h_a of the previous layer to the neuron h_b in the layer H, $w_{h_a,m}^{(out)}$ is the weight of the link from the neuron h_a in the last hidden layer and the output m, $f^{h_c}(.)$ is the activation functions for the hidden layers, f^{out} $()$ is the activation functions for output layer, $m$is the index for output, H_1, H_2 are the number of hidden neurons in the first and second layers, K is the number of inputs, and finally b_k, b_{h_1} and b_{h_2} are the biases of the layers (Kanevski et al. 2009). In this study, a DNN model is applied to design and develop a deep ensembles model to yield both good predictive performance and reliable uncertainty quantification in blast-induced PPV prediction.

The Uncertainty Framework

All predictions have some degree of uncertainty since the predictions obtained from the models are subject to noise and model inference errors. For regression problems, in many situations, target values$Y$ are estimated based upon a set of input features X:

$$Y = f(X) + \epsilon \quad (3)$$

where *f* is the function defining the relationship between$X$and Y, and ϵ is an error term that explains all the unmeasured influences on Y. ϵ is mostly termed as data uncertainty (i.e. aleatoric uncertainty) and its mean is assumed to be 0. As f is not known exactly, statistical models are used to estimate it and Y is predicted from X using the following equation:

$$\widehat{Y} = \widehat{f}(X) \quad (4)$$

where $\widehat{f}$ describes the selected model's estimate for f, and $\widehat{Y}$ represents the resulting prediction for *Y*. In general, $\widehat{f}$ will not be the perfect estimate for f and the produced inaccuracy will introduce model

uncertainty (i.e. epistemic uncertainty). The two sources of uncertainty, which are aleatoric and epistemic, are summarized in Fig. 4 in a linear regression context.

The blue region in Fig. 4 has a high aleatoric uncertainty that occurs due to intrinsic characteristics of the data (i.e. arising from noisy data). As aleatoric uncertainty is caused by the randomness of data, it cannot be reduced by any additional source of information. The epistemic uncertainty, shown as gray regions in Fig. 4, on the other hand, comes from inadequate knowledge (i.e. arising from the noisy model) and is reducible by improving the model using additional information. Uncertainty quantification is critical for providing reliable predictions in a wide range of engineering domains. Predictions made without uncertainty quantification are usually considered untrustworthy.

Deep Ensembles

The deep ensembles model has been proposed as a simple and scalable method to estimate predictive uncertainty estimates from DNNs (Lakshminarayanan et al. 2017). This method uses three simple recipes to quantify the uncertainty. In the first recipe, a probabilistic DNN $p_\theta(y|\boldsymbol{x})$, where θ denotes weights and biases of a DNN, is trained using a proper scoring rule as the training objective. For regression problems, the parameters of a DNN are generally optimized through the minimization of a mean square error (MSE) loss function, which produces only one output value, mean $\mu_\theta(\mathbf{x})$. Thus, the predictive uncertainty, variance $\sigma^2{}_\theta(\mathbf{x})$, cannot be captured by MSE. For this purpose, the negative log-likelihood (NLL) function is used as the scoring rule to design the final layer of a DNN with two outputs, representing predicted $\mu_\theta(\mathbf{x})$and predicted $\sigma^2{}_\theta(\mathbf{x}) > 0$. The observed value is then used as a sample from a Gaussian distribution $\mathcal{N}(\mu_\theta(\mathbf{x}), \sigma^2{}_\theta(\mathbf{x}))$, and NLL function is minimized:

$$-\log p_\theta(y_n|\mathbf{x_n}) = \frac{\log\sigma^2{}_\theta(\mathrm{x}) + (y(\mathrm{x}) - \mu_\theta(\mathrm{x}))^2}{2\sigma^2{}_\theta(\mathrm{x})} \quad (5)$$

where c is a constant term that does not influence the loss minimization process. The second receipt uses the adversarial training for smoothing the predictive distributions and for robustness to out-of-distribution samples. Adversarial training creates a new training example by applying small but deliberate worst-case perturbations. Lakshminarayanan et al. (2017) has used the fast gradient sign method, which has been presented by Goodfellow et al. (2014), as the adversarial training. In this method, small permutations are added to x along a direction where the DNN is probably to increase the loss:

$$\mathrm{x}' = \mathrm{x} + \epsilon sign\left(\frac{d\mathcal{L}}{dx}\left(\theta, x, y\right)\right) \quad (6)$$

where ϵ denotes adversarial learning step ratio which is a small value and L is the loss, for example, $-\log p_\theta(y|\mathbf{x})$. However, Lakshminarayanan et al. (2017) showed that adversarial training has not significantly contributed to some datasets, especially in regression problems. In the third receipt, an ensemble is trained, which averages predictions over multiple DNNs (sharing the same architecture) consistent with the training data, to increase predictive performance and capture model uncertainty. Ensembling the DNNs, which contain some diversity, provides to estimate of model uncertainty. In an ensemble, each member network is trained on the entire training dataset with independent and random parameter (i.e. weights and biases) initializations, and predictions are combined as:

$$p(y|\boldsymbol{x}) = M^{-1}\sum_{m=1}^{M} p_\theta(y|\boldsymbol{x},\ \theta_m) \tag{7}$$

where M is the number of DNNs in the ensemble. The predictions here are considered as a mixture of Gaussian distributions. The ensemble prediction is then approximated as a Gaussian where its mean and variance are the mean $\mu_*(\mathrm{x})$ and variance $\sigma^2{}_*(x)$ of the mixture, which are defined respectively as follows:

$$\boxed{\mu_*(\mathrm{x}) = M^{-1}\sum_{m=1}^{M}\mu_{\theta m}(\mathrm{x})} \tag{8}$$

$$\boxed{\sigma^2{}_*(x) = M^{-1}\sum_{m=1}^{M}\mu^2{}_{\theta m}(\mathrm{x}) - \left(M^{-1}\sum_m \mu_{\theta m}(\mathrm{x})\right)^2 + M^{-1}\sum_{m=1}^{M}\sigma^2{}_{\theta m}(\mathrm{x})} \tag{9}$$

where $\mu_{\theta m}(\mathrm{x})$ and $\sigma^2{}_{\theta m}(\mathrm{x})$ are the output of an individual model for input x. The variance $\sigma^2{}_*(x)$ of the ensembled model is considered as the predictive uncertainty. The overall training procedure of the deep ensembles model is summarized in Fig. 5.

The deep ensembles model approximates the *epistemic* uncertainty (first two terms in Eq. 9) as part of its output and uses ensemble to estimate *aleatoric* uncertainty (last term in Eq. 9). This model is easy to implement and readily parallelizable to decrease the computational cost. Moreover, this method can cope with large-scale distributed computation and requires very little hyperparameter tuning.

Determination Of Blast-induced Ppv Predictive Models

In this study, a deep ensembles model was developed for predicting the blast-induced PPV together with predictive uncertainty quantification in ten quarry sites (Nigeria). An empirical equation and a DNN model were also produced for comparison with the proposed deep ensemble model. All models were implemented in Python code.

Empirical Model

Numerous researchers developed a number of empirical equations to predict the blast-induced PPV. A literature review showed that the most common and widely applied empirical equation is the United States Bureau of Mines (USBM) proposed by Duvall and Fogelson (1962); thus, it was included in the present study to predict blast-induced PPV and is defined as follows:

$$PPV = k\left(\frac{D}{\sqrt{W}}\right)^{\beta} \quad (10)$$

where k and β are site constants and are defined from the multiple regression analysis. In this study, k = 3619.89 and β = 1.4704 were determined as the optimal values of the USBM empirical equation based on all data pairs for the site constants.

Deep Ensembles

To train the deep ensembles model, the original dataset was randomly divided into two non-overlapping sections. The first part was randomly selected to be 80% of the whole data (160 blasting cases) to train the models and the remaining 20% (40 blasting cases) in the second part were used to assess the accuracy of the performance of the model. This process was repeated 5 times to consider the random outputs, which depends on the random parameter initialization of the networks. Input and output variables were normalized to zero mean and unit variance using the following equation to improve the accuracy and to avoid over-fitting of the DNNs:

$$\mathrm{X}_{\mathrm{norm}} = \frac{\mathrm{X} - \mathrm{X}_{\mathrm{mean}}}{\mathrm{X}_{\mathrm{std}}} \quad (11)$$

where X is the datasets to be normalized, $\mathrm{X}_{\mathrm{mean}}$ is the mean, $\mathrm{X}_{\mathrm{std}}$ is the standard deviation of the dataset, and $\mathrm{X}_{\mathrm{norm}}$is the normalized value of the datasets, respectively.

The deep ensembles model uses multiple copies of one network sharing the same structure, each of which is initialized with random parameters. Therefore, a fixed structure was chosen for all networks. The training was performed using the RELU activation function and ADAM optimizer with a learning rate of

0.03, learning decay rate of 0.9, batch size of 100, and epochs of 100. As the deep ensembles model does not require advanced hyperparameter tuning, this study found the relevant hyperparameters by building a number of DNN models with various structures. Once the best DNN structure was determined for predicting blast-induced PPV, which has two hidden layers with 30 neurons in each layer, the number of networks in the ensemble was investigated. Lakshminarayanan et al. (2017) declared that as the number of networks in the ensemble increases, its performance in terms of NLL increases significantly. Figure 6 proves this statement by evaluating NLL as a function of the number of networks.

For this study, 7 networks in the ensemble were considered as the best in terms of computing time and accuracy for blast-induced PPV prediction. Adversarial training was not been applied in this study as it has a little significant additional effect on regression problems.

Results And Discussion

Model verification and evaluation

To validate and measure the performance of the developed blast-induced PPV models, root mean of squared error (RMSE), coefficient of determination R^2, and NLL (Eq. 5) have been used as performance indices:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\mathrm{PPV}_{\mathrm{predicted}} - \mathrm{PPV}_{\mathrm{measured}}\right)^2} \tag{12}$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{n}\left(\mathrm{PPV}_{\mathrm{predicted}} - \mathrm{PPV}_{\mathrm{measured}}\right)^2}{\sum_{i=1}^{n}\left(\mathrm{PPV}_{\mathrm{measured}} - \mathrm{PPV}_{\mathrm{mean}}\right)^2} \tag{13}$$

where n represents the number of data, and $\mathrm{PPV}_{\mathrm{mean}}$ denotes the mean values of the true data. While RMSE and R^2 measure how close the measured data are to the predicted values of a model, the NLL evaluates the predictive uncertainty. The lower values of RMSE and NLL represent the better performance of the prediction model. While the expected value of RMSE is 0, the expected value of R^2 is 1 for an accurate prediction model.

In addition to those metrics, prediction intervals (PI) were evaluated for uncertainty quantification. A PI is a prediction of an interval between lower, $\hat{y}_L$, and upper, $\hat{y}_U$, PI bounds in which a future observation will fall, with a specified degree of confidence level, (1- α):

$$Pr(\hat{y}_{Li} \leq y_i \leq \hat{y}_{Ui}) = (1\text{-}\alpha), 1 \leq i \leq n \tag{14}$$

where n is the number of the samples and α is commonly chosen as 0.01 or 0.05. For the deep ensembles model, PIs values were extracted using Pearce et al. (2018)' s method that trims the tails of the deep ensembles' normal distributions output by the appropriate amount. For empirical equation which is based on multivariate regression, distributions of input, output, and prediction residuals were assumed as Gaussian, and PIs are calculated as:

$$\hat{y}_i \mp t_{\left(1-\frac{\alpha}{2}, N-2\right)} \cdot \mathrm{se}\left(e_i\right) \tag{15}$$

where $\hat{y}_i$ is the produced prediction, e_i is the error of the prediction and $\mathrm{se}\left(e_i\right)$ is equal to $\sqrt{\widehat{\sigma}^2\left(e_i\right)}$, which is also known as the standard error of the prediction. PIs should be as narrow as possible and some portion of data points should be captured (Papadopoulos et al. 2001; Khosravi et al. 2011). In this regard, the prediction interval coverage probability (PICP) is used to count the number of target values captured by the predicted PIs:

$$PICP := \frac{c}{n} \tag{16}$$

where

$$c := \sum_{i=1}^{n} k_i$$

and $k_i = \begin{cases} 1, if \hat{y}_{Li} \leq y_i \leq \hat{y}_{Ui} \\ 0, else \end{cases}$

where k is an n-length vector indicating whether each sample was captured by the predicted PIs; c is the total number of data points captured. There is a direct relationship between PICP and the width of the PIs. Although reasonably large PICP can be easily obtained by spreading PIs from either side, such PIs are too conservative and less useful in practice, because they do not present the variation of the targets (Khosravi et al. 2011). In this regard, mean prediction interval width (MPIW) is used to quantify how wide the PIs are:

$$MPIW := \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_{Ui} - \hat{y}_{Li}) \quad (17)$$

The lower values of MPIW indicate the better performance of the uncertainty prediction.

Evaluating the developed PPV predictive models

The developed blast-induced predictive models were evaluated in terms of, firstly, performance metrics of RMSE, R^2 and NLL. Then, PICP and MPIW were calculated to assess models in terms of PI performance for prediction uncertainty. During this calculation, α was chosen as 0.05, so 95% PI for each data point was computed based on Gaussian quantiles using predictive mean and variance. The performance metrics of the developed models are shown in Table 3.

Table 3
Performance of the developed model to predict blast-induced PPV

Performance indices	Model		
	Empirical	DNN	Deep ensemble
RMSE	24.67	23.566∓0.084	22.674∓0.056
R^2	0.742	0.754∓0.021	0.77∓0.018
NLL	100.68	4.596∓0.148	4.44∓0.092
PICP	0.91	0.9∓0.036	0.95∓0.021
MPIW	2.199	1.779∓0.197	1.769∓0.085

DNN and deep ensembles models provide both prediction and predictive uncertainty on their evaluation metrics, which are demonstrated in Table 3 as mean ± one standard. These models yielded reliable performance in all examined metrics with a low one standard. From Table 3, it is also easy to recognize that the empirical equation showed the worst performance of the three models used in this study, as expected, with an RMSE of 24.67, R^2 of 0.742, and NLL of 100.68. The performance of a single DNN model was lower than the deep ensembles model, i.e., RMSE of 23.566, R^2 of 0.754, and NLL of 4.596. On the other hand, with an RMSE of 22.674, R^2 of 0.77, and NLL of 4.44, the deep ensembles model was the most powerful of the three models developed in this study. Figure 7 illustrates the measured values and predicted mean blast-induced PPV values by the developed models through scatter plots.

Figure 7 shows that even the measured and predicted values of the deep ensembles model had the best convergence on the regression line, the value of R^2 was low because of noisy and high-variable data, which indicates the need to investigate the uncertainty to evaluate precision. In this regard, PIs quality metrics, which are directly related to uncertainty, shown in Table 3 reveal that the deep ensembles model outperformed both the empirical equation and a single DNN model in terms of PICP (0.95) and MPIW (1.769). Moreover, the deep ensembles model achieved the coverage proportion of 95% target, which describes it as a well-calibrated regressor. Figure 8 illustrates how the deep ensembles model produced PIs and captured an important portion of data.

The models were also validated by analyzing their residuals using a boxplot shown in Fig. 9. The negative residuals produced by the empirical equation indicate that it had an underestimation bias compared to the other models. On the other hand, the residuals of the deep ensembles and DNN models had a median close to zero, which denotes no considerable biases were observed for these models.

The findings of this section showed that the deep ensembles model is a powerful and useful model to predict blast-induced PPVs. Moreover, the deep ensembles model gave direct predictive uncertainty prediction, which was reliable and well-calibrated (Lakshminarayanan et al. 2017). It can be used to filter blast-induced PPV predictions to meet certain accuracy requirements. On the other hand, the performance of the deep ensembles model proposed in this study can be improved by collecting more blast-induced PPV cases, since the performance of deep learning models increases with data size according to a power law as shown in Fig. 10 (Zhu et al. 2016).

It is clear from Fig. 10 that deep learning benefits from large amounts of data, whereas the performance of traditional machine learning models tends to plateau with increasing data.

Conclusion

The relevant literature review showed that uncertainty quantification has never been calculated for blast-induced PPV prediction. However, for this type of safety-critical operation, it is crucial to know when to trust a model's prediction and when to be more careful about its output. On the other hand, the application of deep learning in blasting problems still needs to be investigated. Therefore, this study developed a deep ensemble model, which makes use of deep learning, to both blast-induced PPV prediction and predictive uncertainty quantification in ten quarry sites located in Ibadan and Abeokuta areas, Nigeria. The performance of the deep ensembles model and a single DNN models against the empirical equation showed that both of these intelligent models had acceptable prediction capacity and can be used effectively for blast-induced PPV prediction with acceptable error rates. Moreover, the comparison of two models showed that the deep ensembles model was more accurate and provided more reliable predictive uncertainty quantification, with the lowest RMSE (22.674), NLL (4.44), MPIW (1.769), and highest R^2(0.77) and PICP (0.95), than a single DNN model as the ensembling approach improved the prediction performance and quality of uncertainty. The deep ensembles model also achieved the desired coverage of 95%, which shows uncertainty was neither underestimated nor

overestimated. The results of the deep ensembles model can be used to collect more samples where there is high uncertainty prediction. However, this study only considered the D and W parameters in predicting the blast-induced PPV, whereas many features can affect ground vibration, such as powder factor, properties of rock mass, explosive capacity, burden, spacing, stemming, number of rows per delay. These parameters should be incorporated into datasets to obtain more accurate predictions and reliable predictive uncertainty quantification. Finally, as the deep learning models perform better with more data, the deep ensembles model proposed in this study would yield more accurate predictions and reliable predictive uncertainty quantification by adding more data.

Declarations

Funding None.

Conflict of interest

There is no competing interest

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Figures

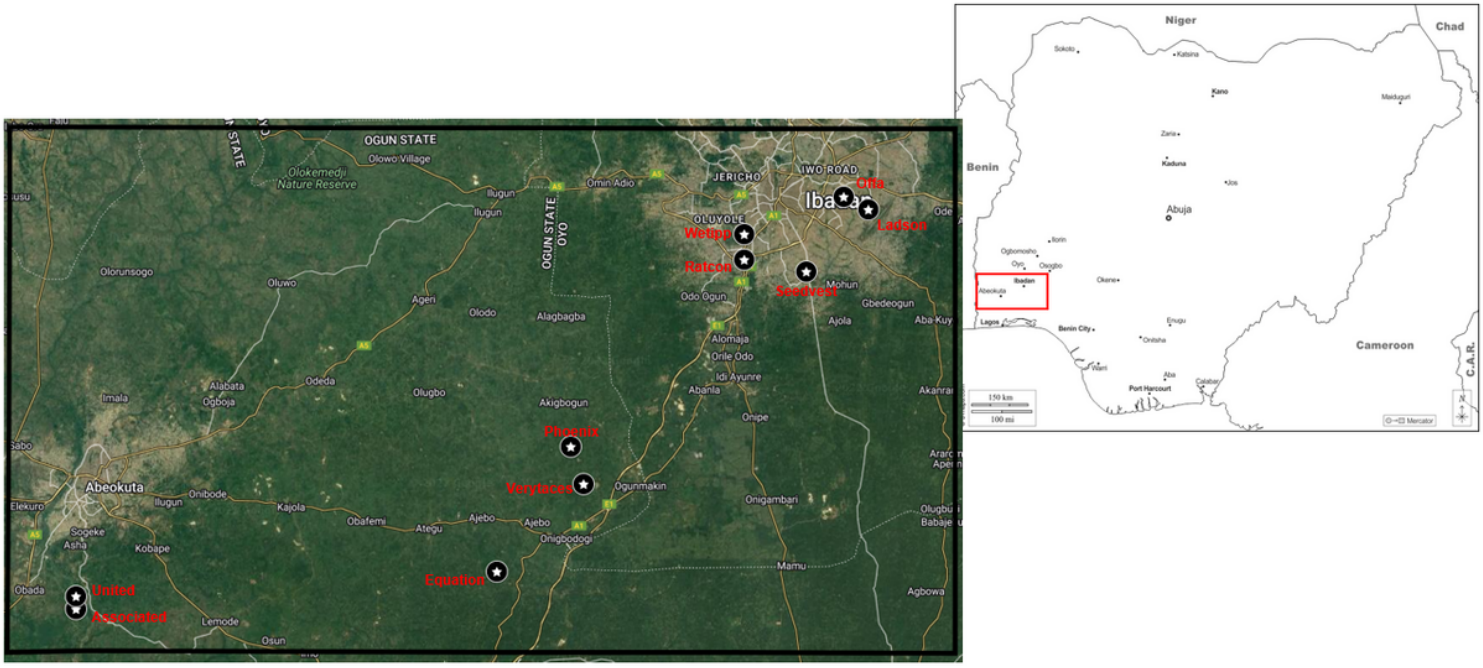

Figure 1

Location map of the ten quarries

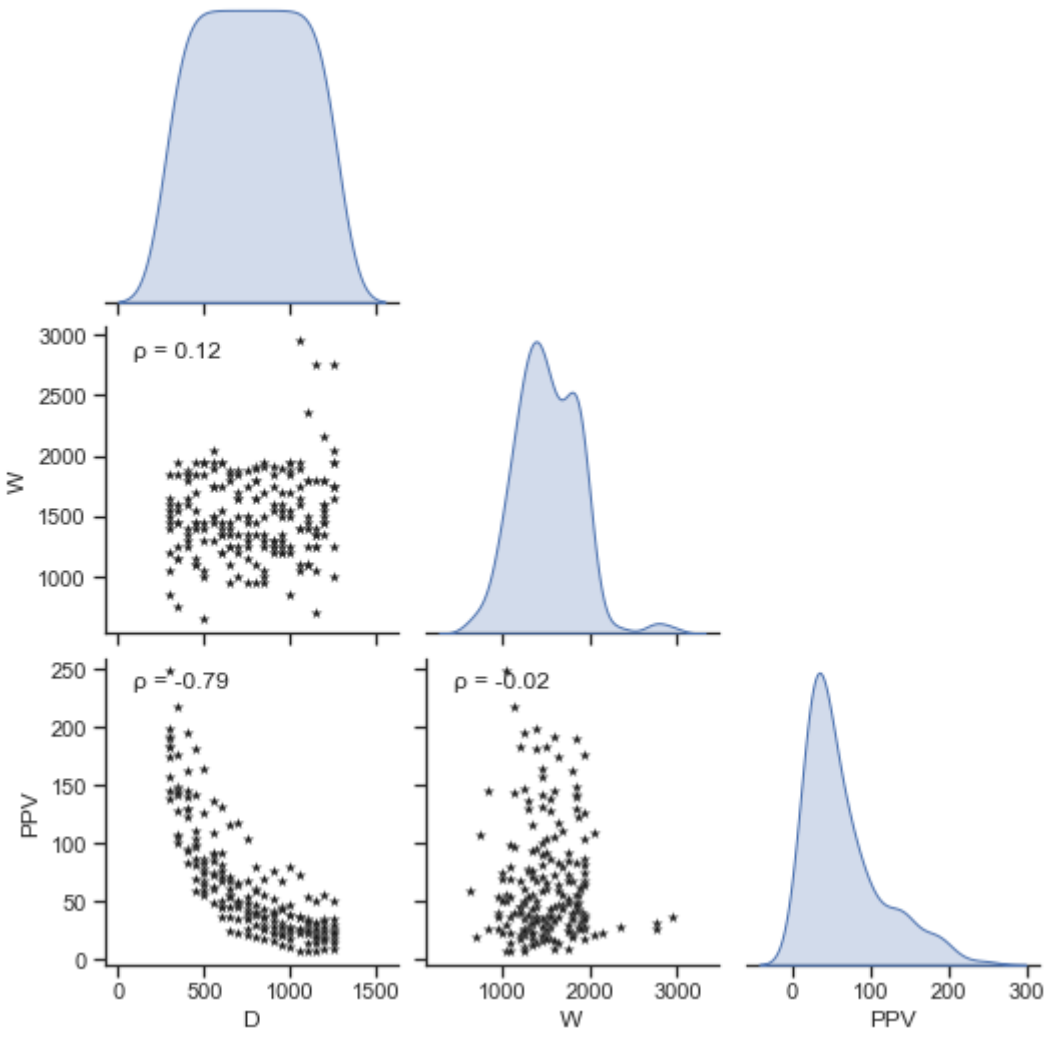

Figure 2

Scatterplot matrix of PPV dataset

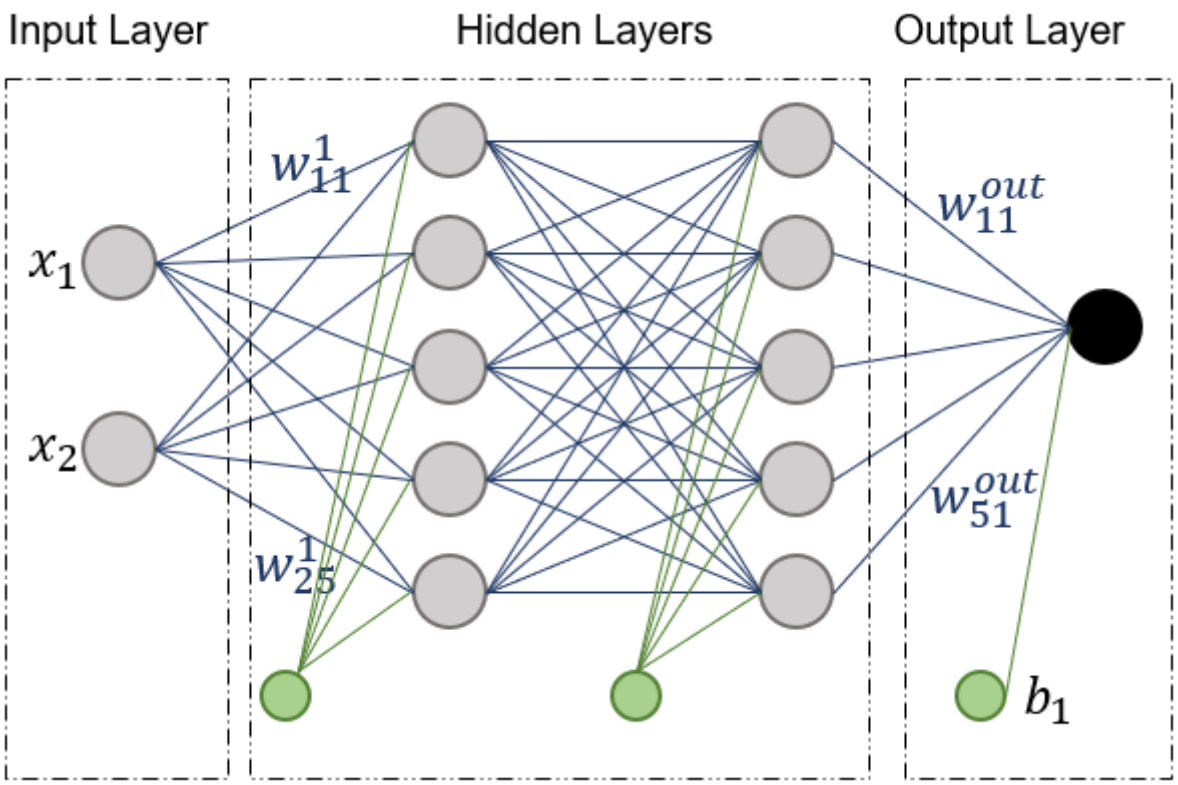

Figure 3

A diagram of a DNN model with two hidden layers. Green circles are bias terms attributed to the layers.

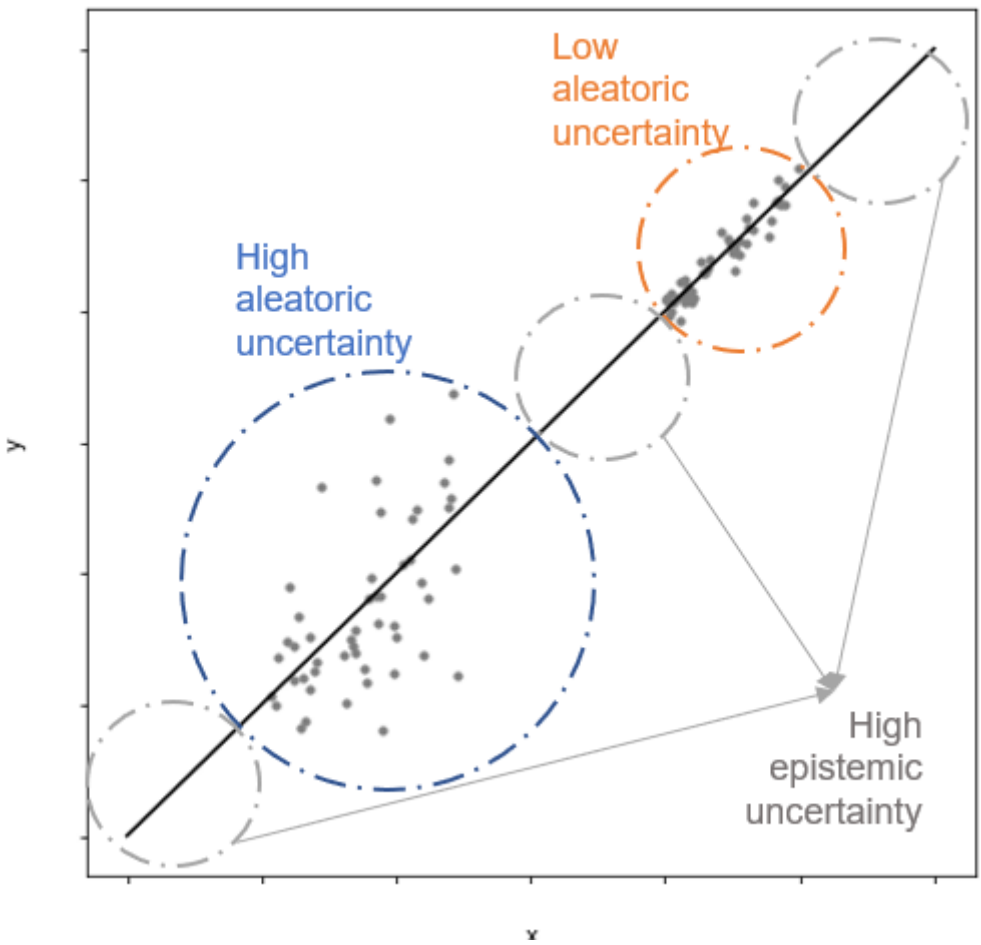

Figure 4

A schematic view of the uncertainty types.

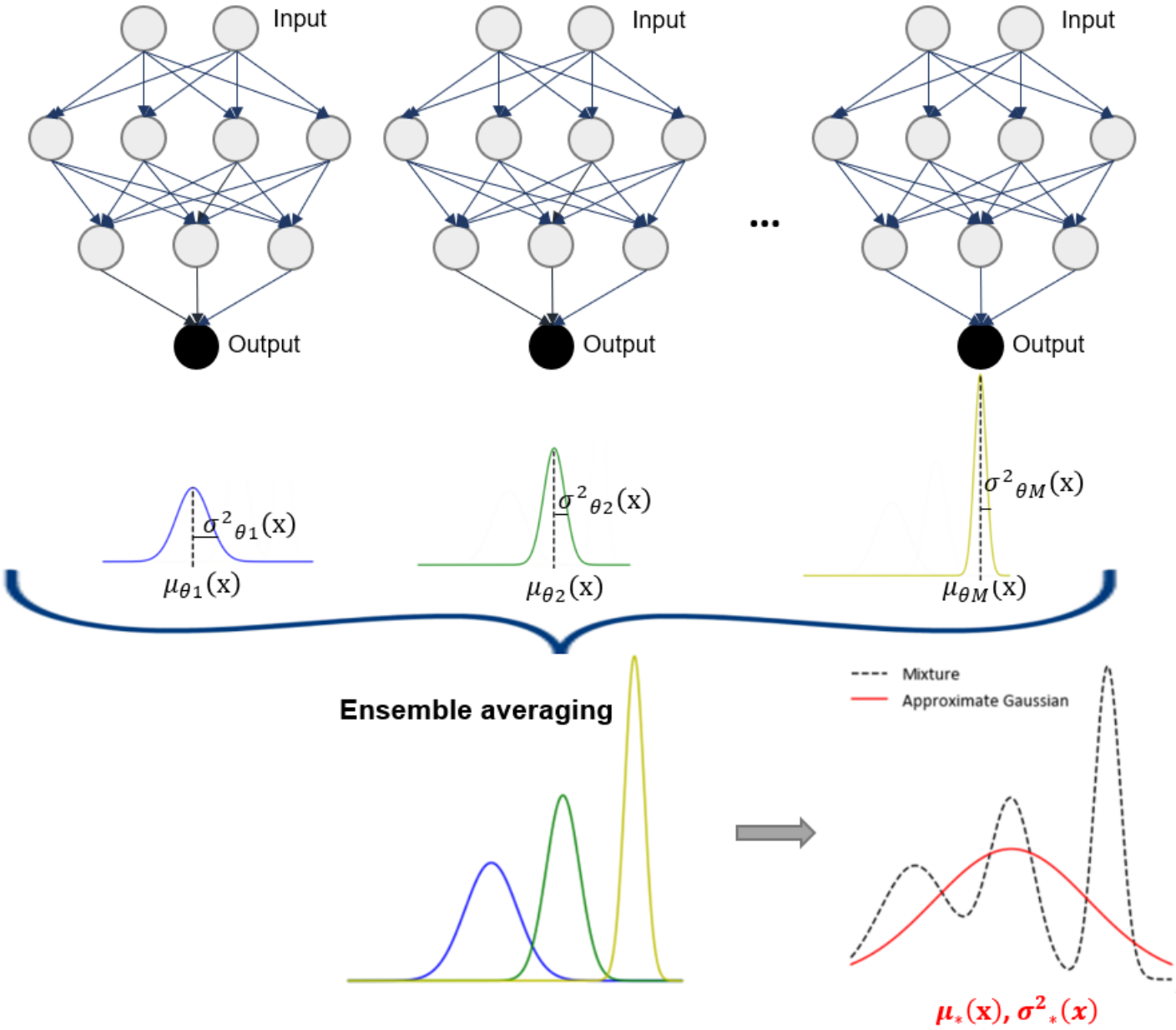

Figure 5

Deep ensembles model with possible networks

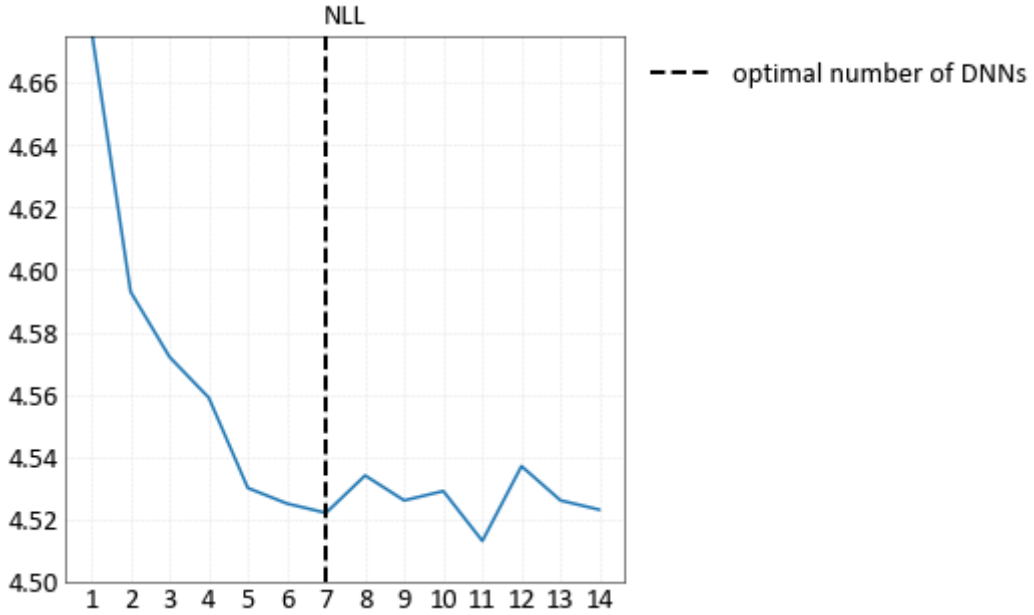

Figure 6

Evaluating predictive uncertainty in terms of the number of networks

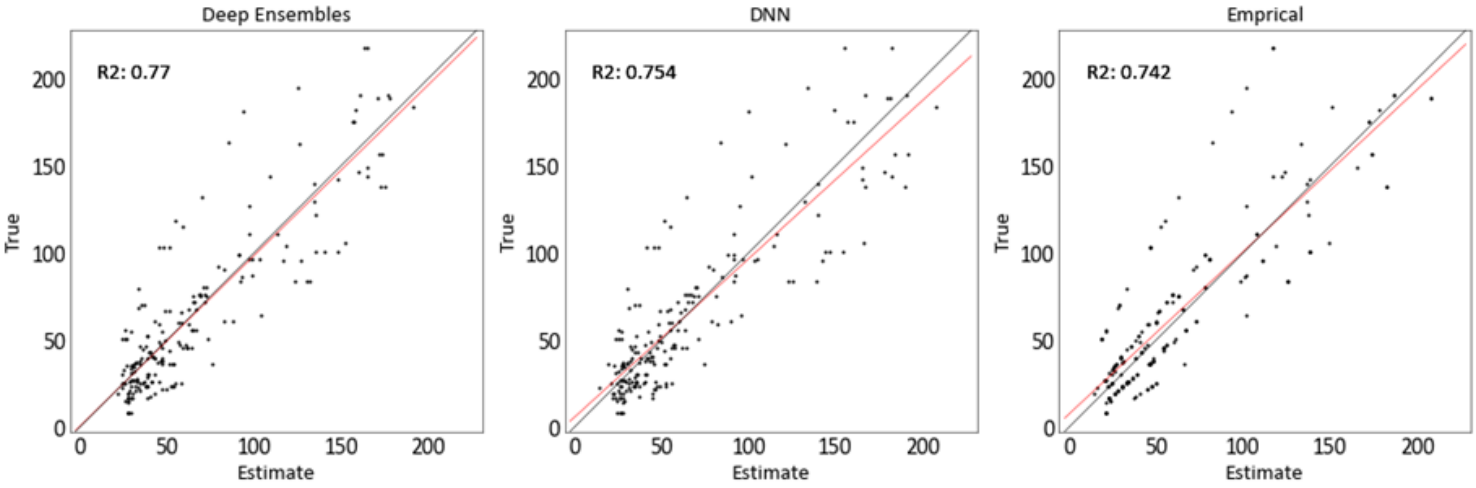

Figure 7

Performance of the developed models for blast-induced PPV prediction

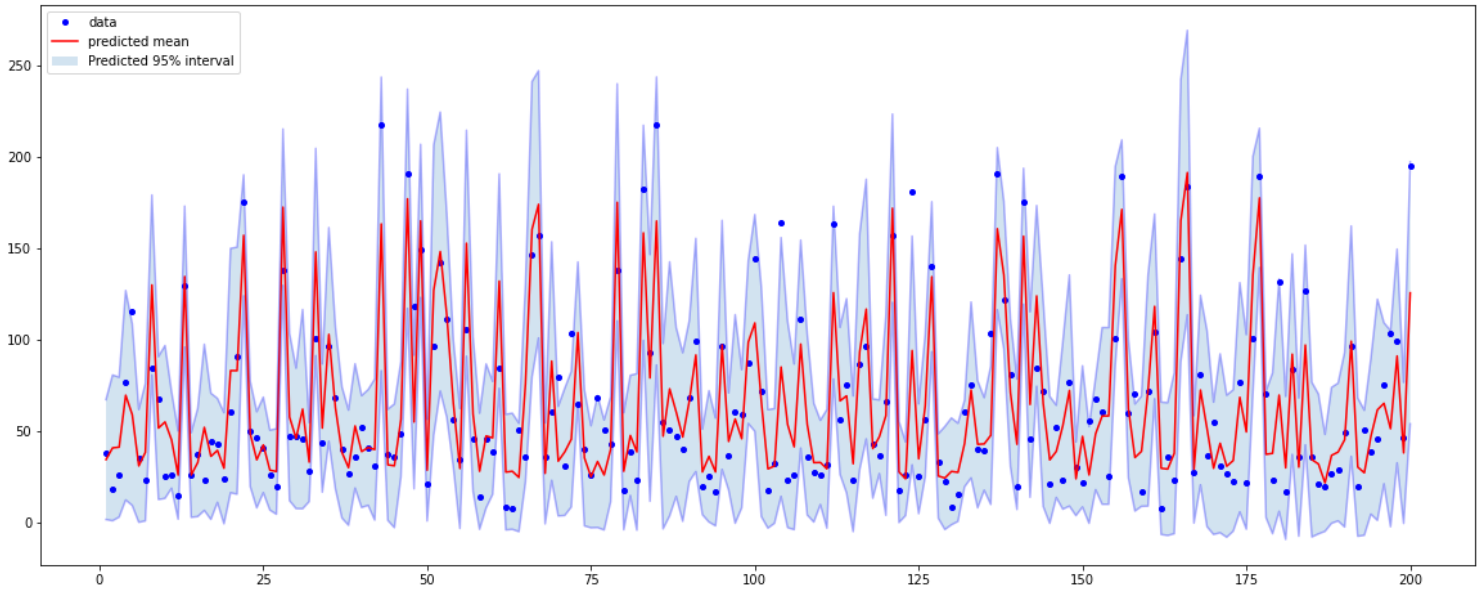

Figure 8

PIs produced by the deep ensembles model for blast-induced PPV prediction

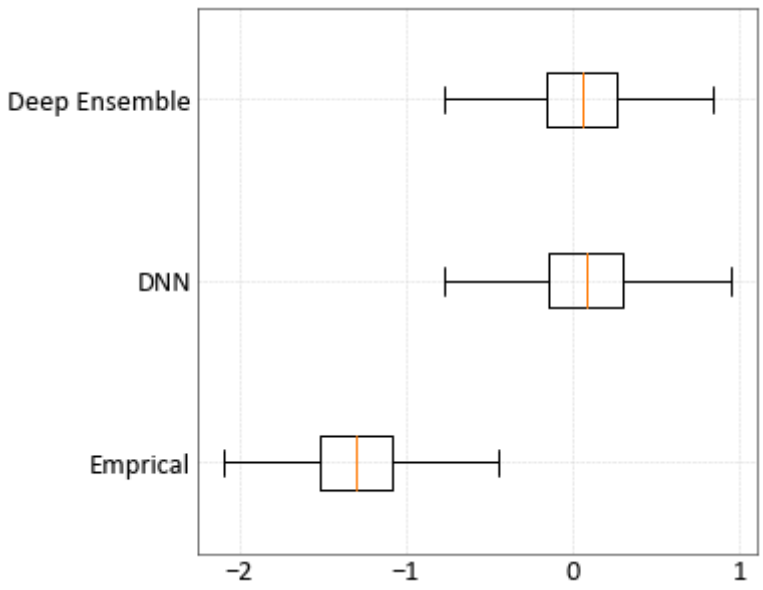

Figure 9

Residual analysis of the models

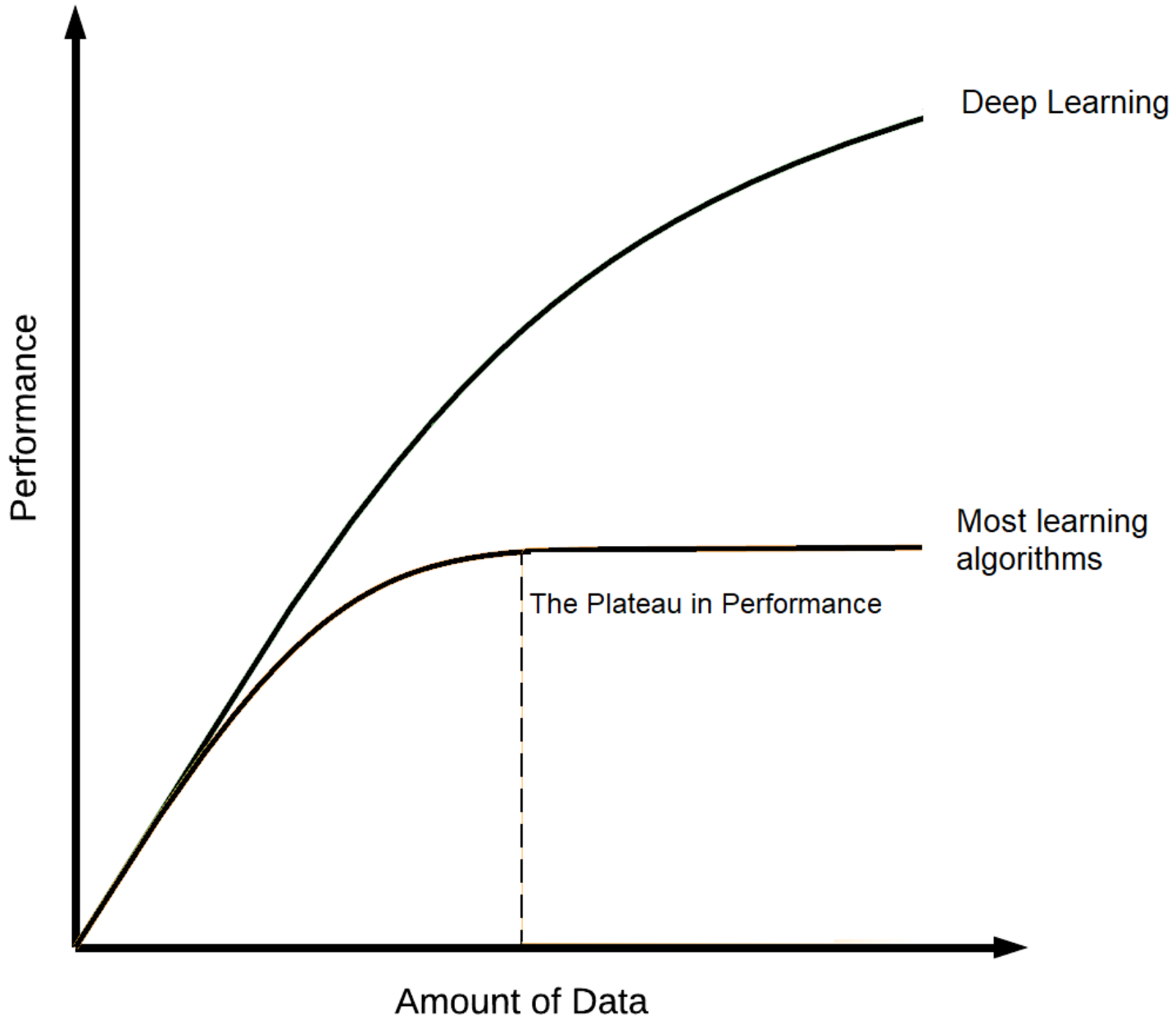

Figure 10

The performance of deep learning by the amount of data (Kraus et al. 2020)