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Prediction of longitudinal wave speed in rock bolt coupled with Multilayer Neural Network (MNN) algorithm

Jung-Doung Yu [1a], Geunwoo Park [2b], Dong-Ju Kim [2c] and Hyung-Koo Yoon*[3]

[1] *Department of Civil Engineering, Joongbu University, Goyang, 10279, Republic of Korea*
[2] *School of Civil, Environmental and Architectural Engineering, Korea University,*
145, Anam-ro, Seongbuk-gu, Seoul, 02841, Republic of Korea
[3] *Department of Construction and Disaster Prevention Engineering, Daejeon University, Daejeon, 34520, Republic of Korea*

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Abstract. Non-destructive methods are extensively utilized for assessing the integrity of rock bolts, with longitudinal wave speed being a crucial property for evaluating rock bolt quality. This research aims to propose a method for predicting reliable longitudinal wave velocities by leveraging various properties of the rock surrounding the rock bolt. The prediction algorithm employed is the Multilayer Neural Network (MNN), and the input properties includes elastic modulus, shear wave speed, compressive strength, compressional wave speed, mass density, porosity, and Poisson's ratio, totaling seven. The implementation of the MNN demonstrates high reliability, achieving a coefficient of determination of 0.996. To assess the impact of each input property on longitudinal wave speed, an importance score is derived using the random forest algorithm, with the elastic modulus identified as having the most significant influence. When the elastic modulus is the sole input parameter, the coefficient of determination for predicting the longitudinal wave speed is observed to be 0.967. The findings of this study underscore the reliability of selecting specific properties for predicting longitudinal wave speed and suggest that these insights can assist in identifying relevant input properties for rock bolt integrity assessments in future construction site experiments.

Keywords: experiment; longitudinal wave speed; Multilayer Neural Network (MNN); rock bolt

1. Introduction

Tunnel structures employ rock bolts for internal reinforcement, enabling the connection of the internal rock mass with the tunnel walls to form a cohesive structure, thus improving stability (Aparna and Bindu 2023, Guzman and Payano 2023). It is essential to evaluate the installed rock bolts to verify they meet the designed load requirements. Non-destructive testing methods are utilized to predict their condition without causing significant deformation to the structure. Among these methods, elastic wave exploration is used to infer the condition of the medium's contact surfaces. This method involves applying sources of compressional and shear waves and analyzing the reflected and refracted waveforms. The analysis, based on speed, frequency, and time-frequency, facilitates the assessment of the medium's condition. However, if the wavelength is significantly larger than the diameter of the target object, the emission of compressional and shear waves can lead to the occurrence of guided waves. Therefore, experiments conducted on sites with installed rock bolts must take these waveforms into account. Guided waves consist of longitudinal and transverse waves, with the longitudinal waves being relatively faster and easier to analyze, which makes them the primary focus for acquisition. As a result, numerous studies aim to infer the degree of grouting cohesion and the condition of rock bolts at construction sites by analyzing the speed and frequency of longitudinal waves (Tacim *et al*. 2023, Liu *et al*. 2024). This research also emphasizes acquiring longitudinal waves and proposes a method to predict their speed using machine learning techniques, in addition to experimental methods.

Machine learning techniques are capable of establishing relationships between dependent and independent variables, often uncovering new mathematical connections that diverge from the physical relationships traditionally recognized by researchers (Min and Yoon 2021, Hong *et al*. 2022, Kim and Yoon 2023). As a result, these techniques are widely utilized not only in construction and geology but also across various fields where establishing relationships between variables has proven to be challenging. The cornerstone algorithm of machine learning, the neural network, utilizes regression analysis between input and output properties to identify output values corresponding to new inputs (Min *et al*. 2023a, Park *et al*. 2023, Al-Swaidani *et al*. 2024). The reliability of these output values hinges on several factors, including the number of nodes within the neural network, the weights assigned to each node, the activation function, and the inclusion of hidden layers. When the model incorporates multiple hidden layers, it is termed a multilayer neural network (MNN), which is

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*Corresponding author, Ph.D., Associate Professor,
E-mail: hyungkoo@dju.ac.kr

[a] Ph.D., Assistant Professor

[b] Ph.D., Postdoctoral Researcher

[c] Ph.D. Student

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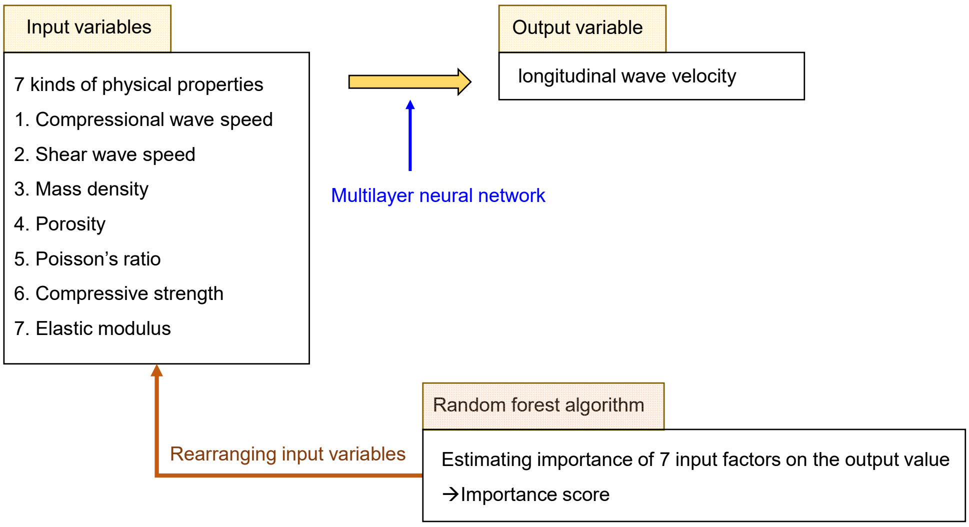

Fig. 1 Overall flowchart of the study

extensively employed to decipher a range of physical phenomena. Both the type and the quantity of input variables significantly influence the MNN's reliability, with an increase in variables often leading to more accurate output predictions. Nonetheless, measuring or collecting data for dozens or even hundreds of input variables can be daunting, necessitating efforts to reduce the number of input variables to a manageable level. This highlights that the presence of characteristic input data that significantly impacts the output variable is sufficient to ensure reliability, even when many variable types are used as input. The random forest algorithm is utilized to ascertain the importance of each input variable, indirectly deducing the significance of variables not included in groups that accurately predict the output value. This approach allows for a rational reduction in the number of input variables, prioritizing them based on their importance and physical correlations. In this study, the random forest algorithm was employed to identify key physical properties for predicting longitudinal wave speed. Subsequently, a multilayer neural network (MNN) was linked to these input variables to verify the results' reliability.

The research detailed the machine learning algorithm used to predict longitudinal wave speed and explored seven types of input variables, as illustrated in Fig. 1. Initially, all seven input parameters were utilized in a multilayer neural network to predict longitudinal wave speed. This was followed by an importance analysis performed using the random forest algorithm. Finally, the input variables were reorganized, starting with the most critical, to assess the reliability of the longitudinal wave speed predictions.

2. Theoretical background

2.1 Multilayer Neural Network (MNN)

In this study, we utilized the neural network algorithm to establish the mathematical relationship between input and output values (Chen and Lai 2023, Zhao *et al.* 2024). The neural network assigns weights and intercept values to each input value, with the goal of predicting values that closely match the actual ones. Different values are assigned across each hidden layer and for each node (Samadi *et al.* 2023, Zar *et al.* 2023). This process facilitates the prediction of longitudinal wave speed and allows for the examination of its reliability by comparison with actual values. The use of multiple hidden layers categorizes this approach as a multilayer neural network (MNN), and the study further investigates the relationship between input and output values through the MNN.

2.2 Random Forest (RF)

The Random Forest (RF) algorithm is grounded in the structure of decision trees and is versatile, applicable to both classification and regression tasks. RF conducts learning by simultaneously using multiple tree branches after randomly sampling from the input variables (Lee *et al.* 2022, Min *et al.* 2023b). This random sampling is designed to extract features in a manner proportional to the square root of the number of input variables. The learning outcome is steered towards reducing error-related indices, such as the Gini coefficient or entropy, in a manner akin to the cost function of an MNN. Consequently, RF mitigates the black box calculation challenge that typically occurs between input and output variables in machine learning techniques. It provides insights into the importance of each variable, thereby indirectly predicting the performance of the MNN.

3. Dataset

The data were obtained through both experimental and numerical analyses. The experiments utilized an accelerated weathering technique, employing the slake durability test on eight types of rock samples collected by drilling at construction sites to induce artificial weathering. Analysis via X-Ray diffraction (XRD) revealed that these rock samples primarily consisted of albite and quartz. While the

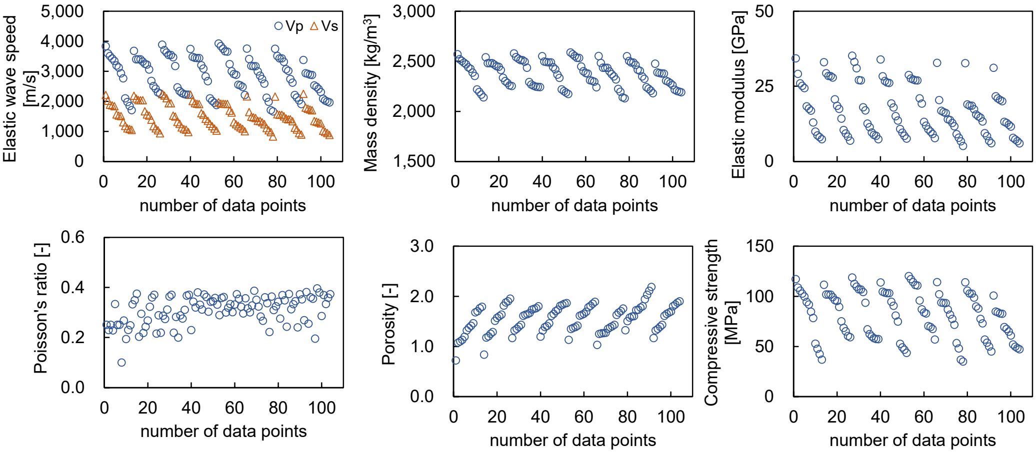

Fig. 2 Distributions of input variables with elastic wave speed, mass density, elastic modulus, Poisson's ratio, Porosity and Compressive strength. This figure was modified after Yu *et al.* (2021), Yoon *et al.* (2022) and Yu and Yoon (2024)

slake durability test traditionally assesses a sample's susceptibility to weathering by enhancing abrasion between rock particles, in this study, it was adapted to expedite the weathering process. Therefore, the experiment simulated not only physical weathering through abrasion with other rock samples but also chemical weathering due to salt crystallization, aiming to ascertain the physical properties under a variety of conditions. The process of artificially inducing both physical and chemical weathering lasted for 24 hours and involved soaking the rock samples in a salt solution (2.5 mol/L) before placing them in an oven at temperatures above 80°C. This method was intended to facilitate the complete formation of salt crystals, thus promoting chemical weathering. Subsequently, the rock samples underwent the slake durability test to incorporate physical weathering considerations, which consisted of three detailed steps in each cycle of physical weathering. This experimental approach is elaborated in Yu *et al.* (2021) and Yoon *et al.* (2022) for further details. At each step, compressional and shear wave velocities were measured with an ultrasonic transducer, and weight and volume were recorded to calculate porosity and mass density. Furthermore, compressive strength, Poisson's ratio, and elastic modulus were estimated using theoretical and empirical formulas. The experiment was structured into three groups, each associating one instance of chemical weathering with three instances of physical weathering, from which measurements and results were derived.

Fig. 2 displays the results from 104 data points obtained from eight samples as weathering progressed. The maximum velocities for compressional and shear waves were recorded at 3928 m/s and 2250 m/s, respectively, with average velocities of 2869 m/s and 1494 m/s. The maximum speed of the compressional wave was approximately 1.7 times faster than that of the shear wave, while the average speed was about 1.9 times faster. The average values for mass density and elastic modulus were reported as 2374 kg/m^3 and 17.27 GPa, respectively, while the averages for porosity and compressive strength were calculated to be 1.55 and 81.66 MPa. Poisson's ratio exhibited a range from 0.1 to 0.4, with an average value of approximately 0.31. The velocities of the elastic waves, mass density, elastic modulus, porosity, and compressive strength showed trends of decreasing or increasing with the progression of weathering, as indicated by the number of data points. Given that eight samples were utilized in the experiment, the dataset was organized into eight distinct groups. However, Poisson's ratio showed a wide variation in data distribution across these groups without a clear trend. This variability indicates that the range of Poisson's ratio, compared to other physical quantities, is relatively narrow, complicating the observation of consistent behavior. Despite this, the weathering process facilitated the derivation of a variety of physical properties, making them adequately suitable as input variables for machine learning techniques. Additionally, the dependent variable V_L was derived through numerical analysis. The propagation of elastic waves was simulated by modeling the rock bolt using a three-dimensional finite element method (FEM) to determine velocity values. The rock mass containing the rock bolt comprises eight nodes and is controlled using hourglassing. Furthermore, an input frequency range of 0 to 50 kHz was applied, and velocity values were estimated after extracting time history data.

4. Result

Physical properties obtained from eight rock specimens, through an artificial weathering process, were analyzed using the MNN method described earlier to predict longitudinal wave speed. Seven physical variables—compressional wave speed, shear wave speed, mass density, elastic modulus, porosity, Poisson's ratio, and compressive strength—were designated as input parameters. The longitudinal wave speed, derived through numerical analysis, served as the output parameter. The MNN architecture was configured with three hidden layers, setting the node counts to 100, 200, and 100 respectively, after hyperparameter tuning. A total of 500 iterations were specified for achieving a reasonable cost function through backpropagation, with Adam optimization and a learning rate set at the commonly recommended 0.001. The dataset comprised 104 input data points, with the train-to-test data ratio adjusted to 7:3, deliberately avoiding shuffle to improve the reliability of repeated calculations and ensure uniform results.

Fig. 3 illustrates the longitudinal wave speed predictions made by the MNN compared to those obtained through numerical analysis, with the 104 data points nearly perfectly aligned along the 1:1 line. The coefficient of determination was reported as 0.9957, showcasing a highly reliable outcome. This indicates that the seven physical properties used as input parameters were effectively leveraged for predicting longitudinal wave speed, suggesting their significant role in the non-destructive assessment of rock bolt integrity in the future. However, given the practical constraints of experimental conditions on-site and the mobility of experimental equipment, it might be challenging to measure all seven physical properties at the same location. This suggests a potential drop in the reliability of longitudinal wave speed predictions if not all seven properties can be ascertained. From a user's perspective, identifying the minimum necessary properties for longitudinal wave speed prediction becomes critical for conducting essential experiments when acquiring all seven properties poses a challenge. While ideally obtaining a complete set of properties is preferred, in scenarios where this is impractical, securing at least the crucial properties for predicting longitudinal wave speed becomes paramount. Consequently, this study employed the RF to explore the impact of the seven physical properties, utilized as input parameters, on the accuracy of longitudinal wave speed predictions.

As previously mentioned, the RF offers the advantage of providing insights into the black box model of the MNN prediction process, elucidating the relationship between input and output parameters. In this study, seven physical parameters were randomly selected, and their importance was inversely calculated based on the variance from the longitudinal wave speed values. The hyperparameters for this algorithm include the number of estimators, minimum samples split, minimum samples leaf, maximum features, and maximum depth of the tree. For this research, only the number of estimators and the maximum depth were adjusted to 100 and 200, respectively, while the rest were left at their default settings. The accuracy of the RF results, reported as 0.995, suggests that fine-tuning just two hyperparameters can achieve high reliability, indicating a well-considered hyperparameter selection.

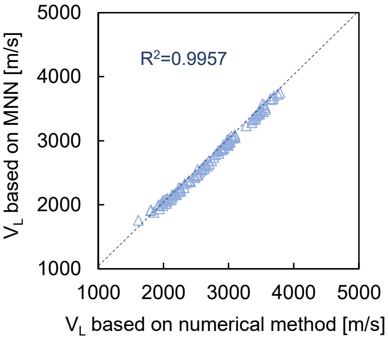

Fig. 3 Comparison between the results obtained from numerical analysis and those interpreted by a Multilayer Neural Network (MNN)

The RF results, depicted in Fig. 4, rank the parameters by their influence on predicting longitudinal wave speed, with the most impactful parameter denoted by an importance score. Elastic modulus, scoring 0.467, emerged as the paramount parameter for predicting longitudinal wave speed, followed by shear wave speed, compressive strength, compressional wave speed, mass density, porosity, and Poisson's ratio, with importance scores of 0.415, 0.040, 0.039, 0.033, 0.006, and 0.001, respectively. The nearly identical importance scores of elastic modulus and shear wave speed underscore their significant role among the physical properties, whereas the other five parameters demonstrated very low importance for the prediction of longitudinal wave speed. Specifically, these five parameters are detailed in a subplot within Fig. 4, with their value ranges extending to the second or third decimal places, indicating their minimal impact on the prediction of longitudinal wave speed. The importance scores effectively distinguish between the group comprising elastic modulus and shear wave speed and the other groups, illustrating the significant influence of these two physical parameters on the prediction of longitudinal wave speed. From a maintenance standpoint, extracting all seven physical properties is optimal for on-site assessment of rock bolt integrity. Nonetheless, under challenging experimental conditions, securing at least the two key parameters—elastic modulus and shear wave speed —is crucial for reliable longitudinal wave speed predictions. In situations where only one property can be acquired due to site limitations, the elastic modulus should be prioritized as an indispensable property, highlighting its paramount importance.

5. Discussion

This study concentrated on developing methods for the easy and efficient evaluation of longitudinal wave speed, which can indirectly indicate the condition of rock bolts.

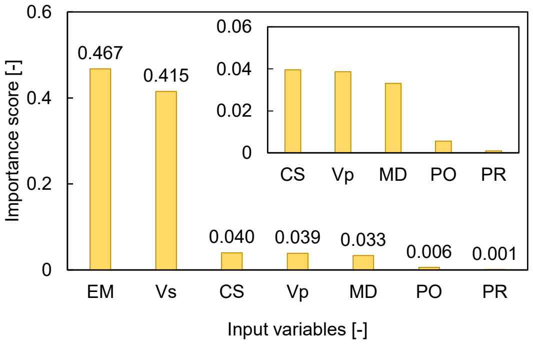

Fig. 4 Distribution of importance scores for seven types of input variables utilized in predicting V_L. The EM denotes the elastic modulus. The V_s and V_p show the shear and compressional wave speeds, respectively. The CS, MD, PO and PR are compressive strength, mass density, porosity and Poisson's ratio, respectively

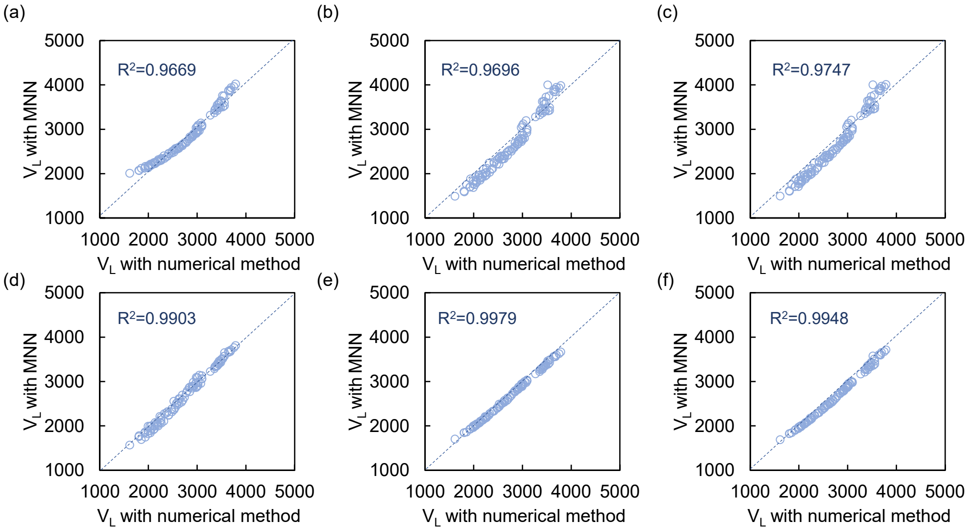

Fig. 5 The outcome of predicting V_L by sequentially accumulating input properties in their order of importance, as determined by random forest analysis: (a) elastic modulus; (b) elastic modulus + shear wave speed; (c) elastic modulus + shear wave speed + compressive strength; (d) elastic modulus + shear wave speed + compressive strength + compressional wave speed; (e) elastic modulus + shear wave speed + compressive strength + compressional wave speed + mass density; (f) elastic modulus + shear wave speed + compressive strength + compressional wave speed + mass density + porosity

While seven physical properties were identified as input parameters, the study also highlighted essential properties that must be secured in challenging environments to enable reliable predictions of longitudinal wave speed. A critical aspect of the research involved quantitatively assessing how the reliability of longitudinal wave speed predictions is affected when solely utilizing the key factors identified by RF results. Consequently, the investigation explored alterations in the MNN's reliability when these important factors were employed as input parameters. According to Fig. 5, the significance order of these factors is elastic modulus, shear wave speed, compressive strength, compressional wave speed, mass density, porosity, and Poisson's ratio. The approach for input parameters was incrementally structured, initiating with the most crucial factor. Initially, the singular input data comprised only the elastic modulus, deemed the most critical factor. Following this, elastic modulus and shear wave speed were the exclusive physical parameters set as inputs, continuing in this fashion by sequentially incorporating properties based on their significance, thus constituting six distinct groups of input parameters. Although the study utilized seven input parameters, the outcomes from employing all seven were consistent with those depicted in Fig. 3; hence, the decision was made to limit the input property groups to six properties.

The distribution of predicted longitudinal wave speeds using the MNN algorithm across groups containing 1-6 physical properties is illustrated in Fig. 5. This figure, akin to Fig. 3, compares the relationship between predicted and actual longitudinal wave velocities, incorporating a 1:1 line to assess the linearity of the outcomes. When solely the most critical property, elastic modulus, served as the input parameter, the predicted longitudinal wave velocities exhibited a slight deviation from linearity, particularly below 2000 m/s and above 3500 m/s. Furthermore, the analysis for groups composed of 2 and 3 key parameters, as depicted in Figs. 5(b) and 5(c), revealed that the MNN tended to overestimate values for longitudinal wave velocities exceeding 3500 m/s. Conversely, groups with more than 4 significant parameters, shown in Figs. 5(d), 5(e), and 5(f), closely aligned with the actual longitudinal wave velocities across all measured ranges. Despite reliable outcomes when using only the elastic modulus as an input parameter, the findings indicate that a minimum of 4 physical properties are necessary to achieve reasonable value predictions across the entire range. The coefficient of determination for each set of results is presented in Fig. 6, facilitating a comparison of the overall reliability. Consistent with Fig. 5's findings, employing only the elastic modulus resulted in a comparatively lower coefficient of determination, which improved proportionally with an increase in the number of input data points. Notably, when the input data encompassed 4 or more properties, the coefficient of determination exceeded 0.99, showcasing high reliability. In particular, utilizing all 7 input data points achieved a coefficient of determination of 0.996, underscoring that reliable longitudinal wave speed predictions are feasible on construction sites by identifying only the 4 pivotal parameters: elastic modulus, shear wave speed, compressive strength, and compressional wave speed. Although utilizing a single property as an input parameter yielded a lower coefficient of determination of 0.967, this outcome could still be deemed highly correlated from a practical standpoint. Thus, securing all 4 physical properties under experimental conditions affords the most accurate longitudinal wave speed predictions. However, in situations where obtaining all properties proves impractical, ensuring the acquisition of at least the elastic modulus is paramount.

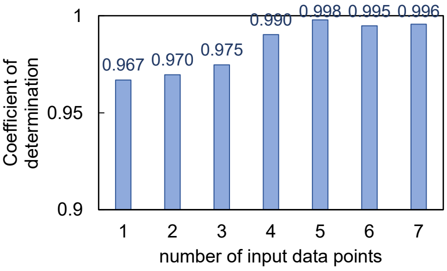

Fig. 6 Change in the coefficient of determination according to the number of input data points

6. Conclusions

This study aimed at assessing the integrity of areas reinforced by rock bolts, a prevalent tunnel reinforcement technique, through the prediction of longitudinal wave speed from a maintenance standpoint. The Multilayer Neural Network (MNN) method was employed for predicting longitudinal wave speed, and the significance of each physical property was evaluated using the Random Forest algorithm. The key conclusions of this paper are summarized as follows:

- The research identified seven physical properties: elastic modulus, shear wave speed, compressive strength, compressional wave speed, mass density, porosity, and Poisson's ratio. These served as input parameters for the MNN, with longitudinal wave speed designated as the output parameter. The MNN analysis produced a coefficient of determination of 0.9957, demonstrating highly satisfactory results.
- To ascertain the impact of the seven physical properties on the prediction of longitudinal wave speed, we applied the Random Forest algorithm. Each property was quantitatively assessed and assigned an importance score. Subsequently, these properties were ranked according to their scores, in the following order: elastic modulus, shear wave speed, compressive strength, compressional wave speed, mass density, and porosity.
- Input groups of physical properties were reassembled based on their importance, and the coefficient of determination for each group was calculated using the MNN algorithm. As anticipated, the findings indicated that the reliability of predictions improved with an increase in the number of physical properties considered. Remarkably, employing just the most critical property, elastic modulus, yielded a coefficient of determination of 0.967.

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