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Evaluating Neural Network Models for Stress-Strain Prediction in Coarse-Grained Soils

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ABSTRACT
Coarse-grained soil plays a crucial role in civil, subgrade, and hydraulic engineering, where its deformation characteristics directly impact structural stability. Traditional triaxial compression tests are essential for studying soil mechanics but face limitations in capturing deformation behavior due to constrained experimental data and fixed test conditions. In response, this study proposes a Bayesian neural network (BNN)-based prediction method to analyze the deformation characteristics of coarse-grained soil while quantifying prediction uncertainty. Using triaxial test data, the performance of artificial neural networks (ANNs), convolutional neural networks (CNNs), and BNNs is compared through data preprocessing, model development, and training optimization. The results demonstrate that BNN effectively captures soil deformation behavior while providing reliable uncertainty estimation, enhancing prediction robustness. This study offers a novel approach for intelligent prediction of coarse-grained soil deformation and provides theoretical support for optimizing civil engineering design.

KEYWORDS
coarse-grained soils; deformation characteristic; deep learning; Bayesian neural network

1 Introduction

In civil engineering, earth-rock construction plays a vital role, with applications spanning foundation engineering, subgrade construction, and hydraulic projects. Coarse-grained soil, a mixture of rock fragments, stone chips, and stone powder, is extensively used in earth-rock engineering due to its superior mechanical properties[1]. Notably, in earth-rock dam construction, it can constitute over 90% of the total material used. As a result, the engineering characteristics of coarse-grained soil are directly linked to dam deformation and stability[2], which in turn impact the safety and reliability of engineering design and construction. Therefore, accurately modeling its mechanical properties is essential.

Research on the characteristics of coarse-grained soil has been a significant focus in civil engineering. Since the 19th century, studies have explored its mechanical properties and testing methods, with the triaxial compression test emerging as a key technique. This method provides stress-strain relationships crucial for engineering applications. Although research on coarse-grained soil in China began later than in Western countries, it has progressed rapidly, particularly in triaxial testing, leading to successful applications in major infrastructure projects such as the Wanzhou Yangtze River Bridge and the Wushan Tunnel.

The deformation characteristics of coarse-grained soil are an important part of its mechanical properties. The mechanical characteristics of coarse-grained soil usually include strength characteristics, deformation characteristics and permeability characteristics, among which the deformation characteristics mainly describe the stress-strain relationship under the action of external forces, such as compressibility, dilatancy, shear deformation and so on. These characteristics are very important for the stability analysis of earth-rock dam, roadbed and other projects, so the deformation characteristics are the key aspects that cannot be ignored when studying the mechanical behavior of coarse-grained soil[3-5]. Therefore, in the field of civil engineering design, it is of great significance to grasp the deformation characteristics of coarse-grained soil deeply for optimizing the design scheme.

The triaxial compression test plays a crucial role in evaluating the mechanical properties and deformation behavior of coarse-grained soils. It facilitates the determination of key parameters such as cohesion (c), internal friction angle (φ), and elastic modulus (E) [6-8], which describe soil responses under different stress conditions. Additionally, these parameters contribute to the formulation of constitutive models for predicting soil deformation and strength. However, conventional triaxial tests and constitutive models are constrained by limited experimental data and fixed conditions, reducing their applicability and generalization to diverse real-world scenarios.

In recent years, artificial intelligence has developed rapidly, and machine learning models can directly learn from data sets the nonlinear complex correlation between features and outputs, and the mechanical properties of engineering soil are satisfying this complex relationship. At present, the machine learning model has made progress in the study of many other soil samples, including coarse-grained soil, and has been paid much attention by soil mechanics researchers[9-11]. Zhang Pin et al. [12] utilized hybrid data from real and simulated triaxial tests to predict stress using confining pressure, strain, and void ratio as input features. They conducted a comprehensive performance comparison of artificial neural networks (ANNs), extreme learning machines (ELMs), and evolutionary polynomial regression (EPR). Zhang Ning et al. [13] employed hybrid data from sandy soils, incorporating stress-strain history as input features, including porosity, confining pressure, and axial stress. They applied the Long Short-Term Memory (LSTM) method to simulate the stress-strain behavior of saturated soils, achieving favorable results. Additionally, they analyzed the model's performance under low-stress conditions. Zhang Pin et al. [14] proposed using Convolutional Neural Networks (CNNs) to extract particle information from DEM-simulated coarse-grained soils, followed by Bi-directional Long Short-Term Memory (BiLSTM) to simulate the overall mechanical behavior of coarse-grained soils.

However, these methods also have certain drawbacks. Typically, ANN-based predictions yield deterministic values, making it difficult to assess the uncertainty of the results. This limitation poses challenges such as handling data noise and missing values, evaluating the reliability of predictions, and interpreting the underlying mechanisms of the results[15]. Although ANNs can achieve accurate predictions, they suffer from issues like slow convergence and susceptibility to local minima[16].

Prediction methods based on Bayesian neural networks (BNNs) not only inherit the advantages of ANNs but also leverage Bayesian inference to handle uncertainty and complexity, thereby enhancing the accuracy and reliability of predictions. Meanwhile, BNNs have achieved significant results across various fields. For instance, Zhang P proposed a modeling strategy for predicting soil properties—a novel application in geotechnical engineering—by integrating BNNs' strong nonlinear fitting capabilities and uncertainty quantification[17]. Bate A et al. employed Bayesian confidence propagation neural networks (BCPNNs) to detect critical signals of adverse drug reactions[18]. Li Mingxuan, Han Hongwei, and others used BNNs to predict permeability at well locations[19]. Bi Chunguang, Wang Jinlong, and colleagues compared BNNs with traditional BP neural networks, concluding that BNNs demonstrated superior early warning capabilities, providing valuable guidance for the prevention and control of maize diseases[20]. Therefore, applying Bayesian neural networks to study the mechanical properties of coarse-grained soils represents an innovative endeavor.

The contributions of this paper are as follows:

● Leveraging ML-based methods to obtain-curves for direct extraction of deformation parameters. In this way, the experiment efficiency can be improved

● The BNN is used to evaluate the forecast results to aid decision making in the actual project

2 Methodology

This chapter aims to systematically describe the basic characteristics of coarse grained soil and its machine learning research methods. Firstly, the basic mechanical properties are discussed. Then, the application of data-driven modeling method in coarse-grained soil research is deeply analyzed, and the machine learning model and algorithm system adopted in this paper are systematically expounded.

2.1 Deformation characteristics of coarse-grained soil

In the field of civil engineering design, a deep understanding of the deformation characteristics of coarse-grained soils is crucial for optimizing design solutions. A systematic analysis of the strain–volumetric strain relationship curve not only enables accurate predictions of potential geological environmental effects caused by fill construction activities (such as differential settlement and displacement) but also provides essential mechanical parameters for structural stability assessments.

Specifically, the axial strain–volumetric strain relationship curve serves the following purposes:

1. Intuitively characterizing the dilative and contractive behavior of coarse-grained soils.

2. Identifying the transition to plastic flow by analyzing changes at different stages of the curve, thereby aiding in the analysis of failure mechanisms.

3. Reflecting the elastic response of the soil within a small deformation range, with the slope of the curve used to calculate the elastic modulus (E), which measures material stiffness.

4. Determining Poisson's ratio (v) by computing the ratio of radial strain to axial strain, which describes the material's deformation behavior under external forces.

Given that strain data are key parameters for evaluating soil mechanical behavior, their measurement accuracy directly affects the reliability of structural analysis results.

2.2 Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are computational models inspired by the structure and functionality of biological neural networks.

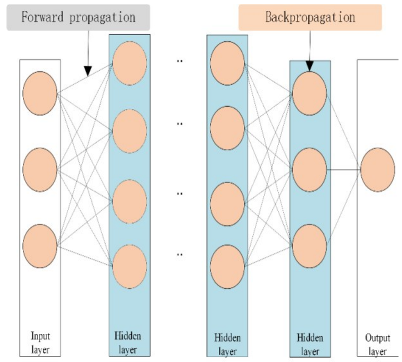

Figure 1 ANN model structure

As shown in Figure 1, they consist of interconnected nodes (neurons) organized in layers, typically including an input layer, one or more hidden layers, and an output layer. ANNs are widely used for function approximation, classification, and regression tasks in various fields.

An ANN consists of multiple layers, where each neuron in a layer receives inputs from the previous layer, applies a weighted sum followed by an activation function, and passes the result to the next layer. The mathematical formulation for a single neuron is:

$$z_j = \sum_{i=1}^{n} w_{ij} x_i + b_i \text{(1)}$$

Where x_i is the input from the previous layer, w_{ij} represents the weight connecting input i to neuron$j$, b_j is the bias term, z_j is the weighted sum before applying activation

Forward Propagation: In a feedforward ANN, the output of each layer is passed to the next layer using:

$$a^{l+1} = f\left(W^l a^l + b^l\right)(2)$$

where a^l is the activation vector from layer l, W^l is the weight matrix, and b^l is the bias vector.

Back Propagation: ANNs are trained using the backpropagation algorithm, which minimizes the error between the predicted and actual outputs by adjusting the weights and biases. The weight updates follow the gradient descent rule:

$$w_{ij}^{l+1} = w_{ij}^l - \eta \frac{\partial L}{\partial w_{ij}}(3)$$

where η is the learning rate.

By utilizing nonlinear transformations and advanced feature extraction, ANNs effectively identify complex data patterns, making them highly effective across various research fields.

2.3 Convolutional Neural Network (CNN)

Convolutional neural network (CNN) By utilizing convolutional operations, CNN effectively capture spatial layers and patterns in data, making them widely used in a variety of applications, including image recognition, natural language processing, and geotechnical engineering. The model structure is shown in Figure 2.

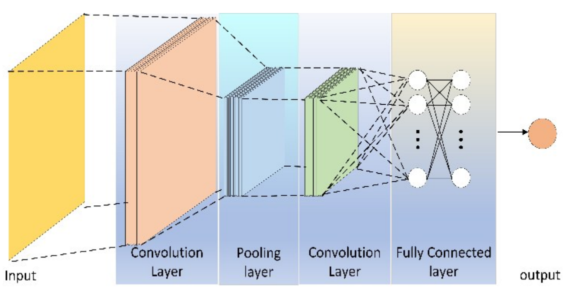

Figure 2 CNN model structure

Convolution Layer: The fundamental operation in a CNN is the convolution, which extracts local features from input data. Given an input matrix and a kernel, the convolution operation is defined as:

$$Y\left(i,j\right) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} X\left(i+m,j+n\right) W\left(m,n\right) + b(3)$$

Where $X(i,j)$ represents the input feature map, $W(m,n)$ is the learnable filter, b is the bias term, M and N are the dimensions of the filter, and $Y(i,j)$ is the output feature map after convolution.

Pooling Layer: Pooling layers reduce the spatial dimensions of feature maps while retaining key information, improving computational efficiency and robustness to small variations. The most common pooling operation is max pooling:

$$P\left(i,j\right)=\max_{\left(m,n\right)\in R}\left(i+m,j+n\right)\left(4\right)$$

where R represents the receptive field.

Fully Connected Layer: After several convolutional and pooling layers, the extracted features are flattened and passed through fully connected layers:

$$O=\delta\left(W_fF+b_f\right)\left(5\right)$$

Where F is the flattened feature vector, W_f and b_F are the weights and biases, and σ is a non-linear activation function (e.g., softmax for ReLU).

2.4 Bayesian Neural Network (BNN)

Bayesian Neural Networks (BNNs) extend traditional neural networks by incorporating Bayesian inference, which allows the model to quantify uncertainty in predictions. Unlike deterministic neural networks that learn fixed weights, BNNs treat weights as probability distributions, providing more robust generalization, particularly in cases with limited or noisy data.

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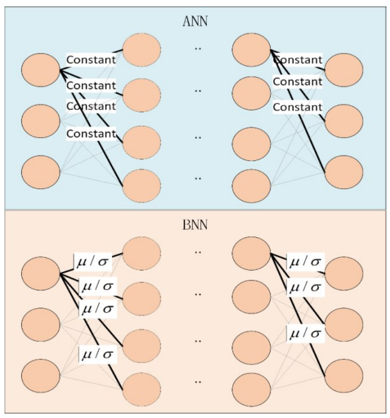


Figure 3 Compare ANN and BNN

In the figure 3, the top half is ANN and the bottom half is BNN. After the optimization, the weight of ANN is a fixed value, while the Bayesian neural network regards the weight as a Gaussian distribution with the mean value μ and the variance δ, and each weight obeys a different Gaussian distribution.

In a standard neural network, given an input X, the output Y is determined by a set of fixed weights W:

$$P\left(Y|X,W\right)\left(6\right)$$

However, in a BNN, the weights themselves are modeled as probability distributions:

$$P\left(W|D\right)=\frac{P\left(D|W\right)P\left(W\right)}{P\left(D\right)}\left(7\right)$$

$P(W|D)$ is the posterior distribution of the weights given the dataset D, $P(D|W)$ is the likelihood function, measuring how well the weights explain the observed data, $P(W)$ is the prior distribution, encoding prior beliefs about the weights, $P(D)$ is the marginal likelihood, acting as a normalization factor.

Training a Bayesian Neural Network：The goal of training a BNN is to estimate the posterior distribution $P(W|D)$, but computing it exactly is intractable due to the complex integral in the denominator:

$$P\left(D\right)=\int P\left(D|W\right)P\left(W\right)dW\left(8\right)$$

Variational Inference (VI): Because the posterior distribution is difficult to calculate, BNN uses variational inference to approximate the posterior distribution.

Variational inference approximates the true posterior $P(W|D)$ with a simpler distribution $Q(W|\theta)$, parameterized by θ. The objective is to minimize the Kullback-Leibler (KL) divergence between the two distributions:

$$KL\left(Q\left(W|\theta\right)\middle\|P\left(W|D\right)\right)$$

$$=E_{Q\left(W|\theta\right)}\left[logQ\left(W|\theta\right)-logP\left(W|D\right)\right]\left(9\right)$$

Instead of directly computing this, the Evidence Lower Bound (ELBO) is optimized:

$$L(\theta)=E_{Q(W|\theta)}\left[logP(D|W)\right]-KL\left(Q(W|\theta)\|P(W)\right)(10)$$

The second term regularizes the weights by keeping $Q(W|\theta)$ close to the prior $P(W)$.

As a result, BNN has several times as many parameters as ANN the ultimate output and uncertainty can be obtained by:

$$E(Y)=\frac{1}{T}\sum_{i=1}^{T}P(Y|X,W)(11)$$

$$CI=E(y)\pm z\times\frac{s}{\sqrt{N}}(12)$$

$$s=\sqrt{\frac{\sum_{i=1}^{N}\left(y_i-E(y)\right)^2}{N-1}}(13)$$

where CI represents the confidence interval, z is the critical value corresponding to a given confidence level and s denotes the standard deviation of the prediction results. The BNN training process is shown in Figure 4

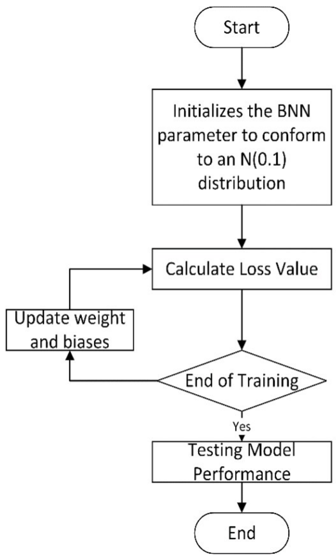


Figure 4 The training process of the BNN

3 Data and Model Architecture

In this chapter, we first introduce the data used and how to obtain it, and then introduce the model architecture used in this experiment.

3.1 Data Collection and Preparation

The experimental data were obtained from existing papers, reports, and other relevant materials available online. In all the materials, although the soils are not identical, they are all coarse-grained soils, with particles larger than 0.075 mm comprising more than 50% of the total soil mass. Additionally, these soils share a similar particle size distribution and gradation, resulting in comparable physical properties.

As shown in Table 1, we extracted feature variables from the experimental data. These features serve as model inputs, with the axial strain of coarse-grained soil as the predicted output.

In triaxial compression tests, the volumetric strain of coarse-grained soils is initially obtained as a continuous value, represented by a curve. A typical axial strain(ε_a)-volume strain(ε_v) curve is shown in Figure 5.

Table 1 the Input Features and Model Output

Feature	unit
Confining Pressure	*MPa*
Container Diameter	*mm*
Container Height	*mm*
Dry Density	*g/cm3*
Void Ratio	%
Gradation	%
Axial Strain	%

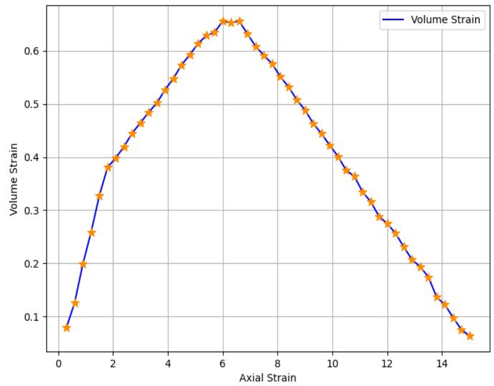


Figure 5 Typical $\boldsymbol{\varepsilon}_a - \boldsymbol{\varepsilon}_v$ curve

In the field of machine learning, data quality is crucial for the accuracy and performance of models. Missing values can compromise data integrity and reliability, ultimately impacting the model's predictive performance. It can be said that the quality of the dataset sets the upper limit of the model's performance. To address missing values in the experimental data, we employed a regression imputation method, using a regression model to predict and fill in the missing values based on other variables.

Additionally, to eliminate the scaling effect of features and speed up the convergence of the model, we applied Min-Max normalization to standardize the data:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (14)$$

where x_{min} and x_{max} are the minimum value and maximum value of the corresponding input feature in the dataset.

3.2 Framework of model

In this experiment, we used a total of 3 models: ANN, CNN and BNN. ANN and BNN have identical input and output layers, with both following a 3-layer architecture. In contrast, CNN differs from ANN and BNN by incorporating a convolutional layer. The parameters for all three models were determined through trial and error.

Trial and Error is a common approach for determining model parameters, where parameters are adjusted repeatedly, and their impact on model performance is observed to optimize the settings over time. In this process, an initial set of parameters is chosen based on existing theories or experience, followed by model training and performance evaluation. If the performance is unsatisfactory, one or more parameters are modified, and the model is retrained and reassessed until the optimal parameter combination is found. Typically, this method involves multiple iterations, as different parameter settings can influence the model's convergence speed, accuracy, or generalization ability. Therefore, it requires exploration within a defined range until the best performance is achieved. The specific parameters of the model are shown in Table 2.

Table 2 Configurations of three models

configuration	ANN	BNN
network layers	4	4
Architecture	11-256-50-1	11-256-50-1
Activate function	ReLU	ReLU
learning rate	0.005	0.005
epochs	3000	3000
batch size	1500	1500
optimizer	NAdam	NAdam
Initial weight	GU	$N(0,1)$
Initial bias	0	$N(0,1)$
T	---	40

configuration	CNN
convolutional layers	$64 \times 10{,}5 \times 128$
maxpool layers	$5 \times 64{,}4 \times 128$
fully connected layers	50-1
learning rate	0.001
epochs	3000
batch size	1500
optimizer	NAdam

Activate Function: ReLU (Rectified Linear Unit) was chosen as the activation function:

$$ReLU = f(x) = \begin{cases} x, & x > 0 \\ 0, & x \le 0 \end{cases} \quad (15)$$

3.3 Model evaluation index

Three main evaluation indexes were used in this experiment: Mean Absolute Error(MAE), Mean Absolute Percentage Error (MAPE), and Coefficient of Determination (R2).

$$MAE = \frac{1}{m}\sum_{I=1}^{N}\left|y_i^p - y_i^a\right| \quad (16)$$

$$MAPE = \frac{1}{N}\sum_{I=1}^{N}\left|\frac{y_i^p - y_i^a}{y_i^a}\right| \times 100\% \quad (17)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i^p - y_i^a\right)^2}{\sum_{i=1}^{n}\left(y_i^a - \bar{y}_i^a\right)} \quad (18)$$

y_i^p represents the predicted value. y_i^a denotes the actual (true) value, $\bar{y}_i^a$ is the mean of the predicted results, and N is the number of data points.

The most important indicator is R2, which reflects the overall fitting effect of the model and facilitates the comparison of different models.

4 Experiment

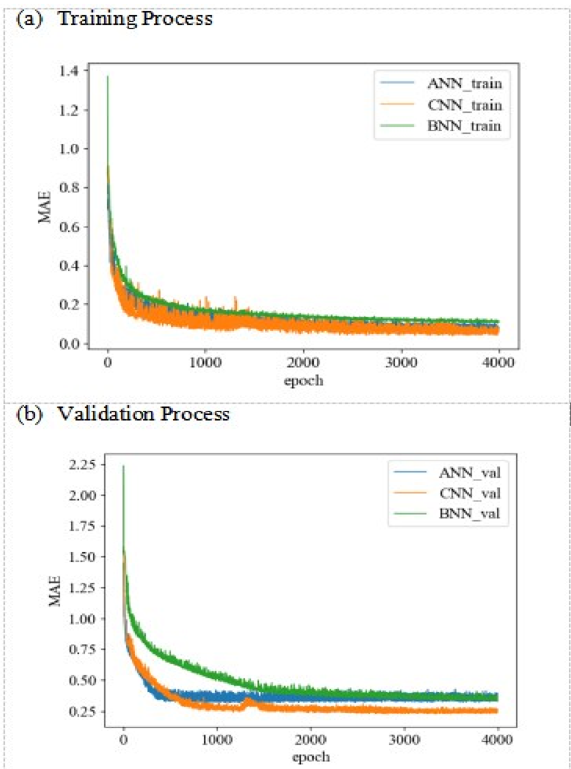
Finally, we compare the ANN, CNN, and BNN based on their training and test results, evaluating their generalization ability and engineering significance.

4.1 Model training and testing performance

The evolution of losses in both the training and validation sets during model training is shown in Figure 6.

As shown in Figure 6, it can be observed that BNN has the slowest convergence, while ANN converges the fastest. This is because the network architecture directly influences the model's performance. Due to the larger number of parameters in BNN, its convergence is slower.

Training Process



4.2 Model performance

Table 3 Performance of Models

Model	Training			Testing		
	MAE	MAPE	R2	MAE	MAPE	R2
ANN	0.062	6.5%	0.984	0.255	22.3%	0.813
CNN	0.085	10.7%	0.951	0.261	20.4%	0.846
BNN	0.115	12.5%	0.903	0.302	26.2%	0.795

As shown in Table 3, ANN performs best on the training set but relatively poorly on the test set. This is primarily because ANN relies on fully connected layers, which are ineffective in capturing the local features of coarse-grained soil data. As a result, its generalization ability is weaker, making it prone to overfitting.

In contrast, CNN achieves the best prediction performance on the test set. This is due to the complex mechanical properties of coarse-grained soil, which exhibit strong spatial correlations and local features—characteristics commonly encountered in civil engineering. By leveraging convolutional operations, CNN effectively extracts local patterns and hierarchical features from the data, allowing it to learn complex relationships more efficiently. Consequently, CNN demonstrates superior generalization ability and outperforms ANN and BNN on unseen data.

As shown in Figure 7, BNN is distinguished by its capability for uncertainty modeling. Instead of merely providing point estimates, it also outputs confidence intervals, making its predictions probabilistically interpretable. BNN focuses more on trend prediction; compared to ANN and CNN, it enhances model robustness by incorporating additional uncertainty. However, this comes at the cost of sacrificing a certain degree of prediction accuracy in exchange for quantifying uncertainty. This characteristic makes BNN particularly advantageous in engineering applications that require risk assessment and reliability analysis.

ANN Prediction Curve

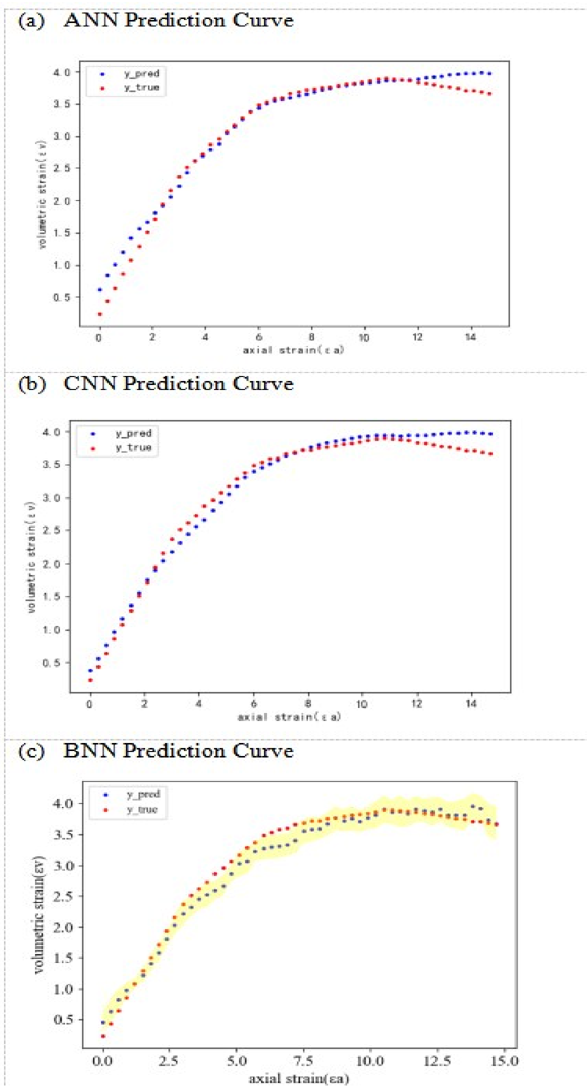


Figure 7 PREDICTION CURVE

5 Conclusion

This paper investigates a machine learning-based method for predicting the deformation characteristics of coarse-grained soil and compares the performance of artificial neural networks (ANN), convolutional neural networks (CNN), and Bayesian neural networks (BNN) in predicting the strain-volume strain curve from triaxial tests. The results indicate that while ANN and CNN effectively capture the strain-volume strain relationship, they struggle to quantify prediction uncertainty. By leveraging Bayesian inference, BNN not only maintains high prediction accuracy but also provides uncertainty quantification, thereby enhancing the reliability of predictions. BNN demonstrates robustness in practical engineering applications by mitigating the effects of data noise and missing values on model performance, offering valuable insights for future engineering applications and research.

Given that CNN achieves the highest predictive accuracy, future research should focus on integrating uncertainty quantification into CNN models to enhance the application value of deep learning in civil engineering.

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