EAI Endorsed Transactions
on Internet of Things
Research Article EAI.EU

Consolidation Coefficient of Soil Prediction by Using Teaching Learning based Optimization with Fuzzy Neural Network

K. Kalaivani[1,*], D. Mohana Priya[2], K. Veena[3], K. Brindha[4], K. Karuppasamy[5], K.R. Shanmugapriyaa[6]

[1]Department of Artificial Intelligence and Data Science, Coimbatore Institute of Technology, Tamilnadu, India
[2]Department of Computer Science and Engineering, Sri Eshwar College of Engineering, Tamilnadu, India
[3]Department of Computer Science and Engineering, Akshaya College of Engineering and Technology, Tamilnadu, India
[4]Department of Computer Science and Engineering, RVS College of Engineering and Technology, Tamilnadu, India
[5]Department of Computer Science and Engineering, RVS College of Engineering and Technology, Tamilnadu, India
[6]Department of Artificial Intelligence and Data Science, Coimbatore Institute of Technology, Tamilnadu, India

Abstract

A key factor in constructing buildings leaning on soft soil is the consolidating coefficient of the soil referred as Cv. It is a crucial lab-measured engineering parameter utilized during the design and verification of geotechnical structures. Nevertheless, experimental experiments take a lot of time and money. In this study, the is projected using Fuzzy Neural Network (FNN) with optimized feature selection using Teaching Learning-based Optimization, estimating Cv as the most crucial step (TLO), which has enhanced the quality of the prediction model by removing unnecessary characteristics and relying solely on crucial ones. The experimental results demonstrate that the projected FNN, followed by the Multi-layer Training algorithm Neural Network (MLP), Impact of changing Optimization (BBO), a support vector regression (SVR), Back - propagation algorithm Multi-layer Training algorithm Bayesian Network (Bp-MLP Neural Nets), has the highest predictive validity for the prediction of (Root Mean Squared Error (RMSE)= 0.379, Mean Absolute Error (MAE) = 0.26, and coefficient of determination r = 0.835). Hence, it can be said that even if all used models perform well in predicting the soil consolidation coefficient, the FNN-TLO performs the best.

Keywords: Machine learning, Fuzzy neural network, Teaching Optimization Based on Learning, Consolidation coefficient, feature selection

Received on 07 November 2023, accepted on 22 January 2024, published on 31 January 2024

doi: 10.4108/eetiot.4990

*Corresponding author. Email: kalai.vani980@gmail.com

1. Introduction

Understanding the soil's consolidation rate is essential for a settlement study on saturated fine-grained soil [1]. From a geological and geo-environmental engineering perspective, it is a crucial metric for assessing soil properties. It is mostly employed to estimate settlement in clay layering. It is possible to test the coefficient of consolidation in a laboratory, but it takes a lot of time and space. Hence, automated consolidation coefficient prediction is helpful [2].

The researchers have thoroughly investigated the relationship between consolidation factors and crucial soil characteristics [3]. Based on piezocone experiments, one of the pioneering efforts in the prediction of the rate of consolidation was carried out [4]. An ANN-based technique for predicting soil settling was described by *Sivakuganet al*. [5]. A strategy for ultimate consolidation settling employing a stress distribution ratio was proposed by *Ishikura et al*. [6].

Due to its successful performance, the literature has suggested several research studies for determining soil parameters using machine learning approaches [7–11]. Since they can provide accurate forecasts, these techniques have been quite popular during the past ten years. To forecast the kinematic viscosity features from fundamental soil variables, an artificial neural network (ANN) model was developed. Its inputs included naturally produced moisture, shrinkage boundary, relative density and specific gravity [12] described an approach for estimating the soil consolidation coefficient that makes use of ANN [13] proposed methods for forecasting the consolidation coefficient using soft computing.

When a model is constructed utilizing uninteresting, noisy, and irrelevant information, its accuracy suffers. By removing the unnecessary variables using feature selection methods, this performance may be improved [14, 15]. The most relevant characteristics that should be utilized to train models can be selected using feature selection approaches. To forecast the coefficient of consolidation, this research suggested using TLO-based feature selection combined with FNN. Tan Vu-LachHuyen in Liberia and the Ha Noi-Hai Phong turnpike construction sites provided samples that were used to assess the amount of compressibility (%), clay (%), moisture (%), the perfect amount of moisture (%),permeability index (%) and apparent viscosity (%). The results from the suggested FNN-TLO are then compared with those from other prediction models. A maximum of 164 soil specimens were collected for laboratory examination. The models that were used to determine the permeability coefficient employed the laboratory tests as input data. Mean Absolute Error, root Mean Square Error, and the correlation coefficient (r) were utilised to evaluate the models' precision. Further subsections have covered all of the techniques employed in the article in detail.

2. RELATED WORK

The contraction index, hydraulic conductivity, and shrinkage boundary were three basic index variables[16] examined concerning the Cv of remolded soils. These techniques, however, have several drawbacks: (1) only dealing with small and simple data input; (2) only constructing basic quantitative relationships between the Cv and a few other factors; (3) finding effective ways to deal with huge data; and (4) only dealing with small and simple input data. Algorithms for machine learning have been created and used recently to address a wide range of real-world issues in several industries [17–23]. It explores massive data using data mining techniques, enabling it to handle difficult issues [24, 25]. In their investigation and comparison of ANN [25] and decision trees (DT) for evaluating sound soil strength [26] investigating the use of Operational Networks for determining clay's residual strength and results demonstrate that the proposed method performs better than the ANN but worse than the (SVM Support Vector Machine). Using probabilistic neural networks, *Kiran et al* [27] estimated the soil's shear strength parameters such as cohesion (c) and internal friction angle (φ) and PNN is effective in calculating the soil shear strength. Erzin and Ecemis [28] used the ANN to successfully predict the conical friction coefficient of fine sand soils. In [29], *Javdanian and Lee* evaluate the application of NF (Neural Fuzzy) and compared with the ANN to the problem of determining the compressive strength without confinement of residual soil stabilised with polycarbonate. *Pham et al.* [30] used and particularly in comparison the GANFIS (Genetic Algorithm-Adaptive Network-based Fuzzy Induction System), the PANFIS (Particle Swarm Optimization-Adaptive Network-based Fuzzy Supervised Learning), the ANN, and the SVM to anticipate the tensile resistance of soft soil based on parameters like plastic viscosity, polymers index, sandy loam, median value, moisture levels, and saturation level as prognostic indicators.

To achieve this goal, a mixed MLP-BBO model based on the Deep Convolutional Neural System and Phenomenon Optimizing (BBO) for the predictions of the of soils was created by Binh Thai Pham et al. A few ground/test center studies for various types of soils may be required to confirm the proposed model's predictions of the ratios at other project sites. Multiple line regression (MLR), ANN, supporting vector regression (SVR), and ANFIS are machine learning methods that Mittal et al. [31] use to estimate the coefficient of consolidation. In addition, many feature selection methods have been used, including RF-RFE, Mutual Information, and the LASSO algorithm (Least Absolute Wastage and Selection Operator). By removing unnecessary characteristics and using just the crucial ones while creating the prediction models, feature selection strategies have been found to boost the accuracy of prediction models. Experimental findings demonstrate that the suggested strategy produced superior outcomes to others.

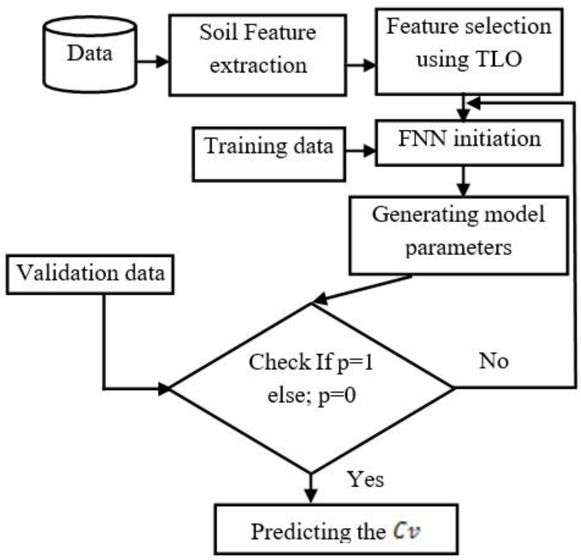

Figure 1. The architecture of the proposed FNN-TLO

3. PROPOSED METHOD

Because there is less uncertainty regarding the underlying link between the variables and the data structure, the FNN is used in this study to assess and forecast the coefficients of consolidation. Fig. 1 depicts the whole procedure. All the solid variables are first taken out, including things like sampling depth, mineral composition, moisture content, moisture content, compressibility, plastic viscosity, and fluidity index. The feature selection process is then started to increase prediction accuracy. Soil characteristics are retrieved, and the most significant ones are chosen. Following the use of FNN to validate the training samples, a coefficient of the soil is projected, which has an input layer, hidden layers, and an output layer.

Data

The Cv of soil is influenced by various features, including the topography, vegetation, and fluid and soil properties. Yet, including these variables in modeling might complicate the model, contradicting the abstraction principle, a fundamental idea in model construction. As a result, the most significant variables were identified and used as modeling process input parameters. FNN was created utilizing the retrieved features, and each feature's importance for the forecasting model was empirically evaluated. As a result, utilizing TLO, the features that contain crucial information have been chosen, and the extraneous features have been removed.

A proportion of granules in soil samples was used to calculate how much clay was present. The amount of moisture was determined using a gravimetric method. The Casagrande device determined the liquid and plastic boundaries [32]. Calculating the fineness modulus (P) is as follows:

$$P = Lt - Pt \tag{1}$$

Where Pt is the plastic boundary and Lt is the liquid boundary. The liquidity index (L) gauges how near a soil sample's water content is to its Zetterberg boundaries. The formula is as follows: [32]

$$L = \frac{Wc - Pt}{Lt - Pt} \tag{2}$$

Here Wc stands for natural density of water and soil reaches its liquid boundary when its fluidity index reaches 1, acting like a liquid, and reaches its plasticity index when it reaches 0. Water content below the plastic boundary is indicated by the liquidity index's negative values. [33]. Samples ranged in depth between 1.6 m to 78.5 m. The soil samples included around 5.70% and 64.00% clay. The range of soil moisture is 15% to 110%. The minimum and maximum values (in %) of the LL and plastics boundary were 18.90 and 12.20, respectively. The minimum and highest percentages of the plasticity and liquidity indices, respectively, were 5.14 and 0.08 and 88.84 and 2.90.

TLO [34], like the majority of other transformational optimization algorithms, is a populace-based computation driven by the classroom learning experience. The searching method may be divided into dual phases: the instructional and the exploratory. In the initial stage, students understand from a teacher; in the second, they study through their peers (i.e., soil features). The instructor ($Cv_{teacher}$).) is regarded as the finest arrangement across the board. As an alternative, during the instructor stage, pupils benefit from the teacher, at this point, the teacher seeks to improve effects on various individuals (Cv_i) by increasing the average Impact of the class (Cv_{mean}) in the direction of the instructor ($Cv_{teacher}$). Two arbitrarily generated parameters, rand and $\mathbb{T}f$, are coupled in the refresh's recipe for the structure."Cv_i" to maintain the pursuit's stochastic characteristics.

$$Cv_{new} = Cv_i + rand.(Cv_{teacher} - \mathbb{T}f.Cv_{mea} \tag{3}$$

Where $\mathbb{T}f$ →a teaching factor value will be 1 or 2 and rand →a randomly chosen value between 0 and 1:

$$\mathbb{T}f^i = round\,[1 + rand\,(0,1)\{2 - 1\}] \tag{4}$$

Moreover, [35,36] the new and current solutions for Cv_{new} and Cv_i →i. The students seek to construct their data by interacting with others in the second step, which is known as the student stage. Thus, a person adopts new knowledge if others have access to more information than they do. The understudy Cv_i works sporadically with another understudy $Cv_j (i \neq j)$ during this phase to develop their understanding. In the case when $Cv_j$is superior to $Cv_i (i.e. f(Cv_j) < f(Cv_i)$ for minimization issues), Cv_iIt is shifted in the direction of Cv. If not, it is shifted away from Cv:

$$Cv_{new} = \begin{cases} Cv_i + rand.(Cv_j - Cv_i) & if\ f(Cv_i) > f(C \\ Cv_i + rand.(Cv_i - Cv_j) & if\ f(Cv_i) < f(C \end{cases} \tag{5}$$

If the new approach Cv_{new} It is superior. It is accepted by the general public. The k top ranking features are chosen after the mutual information between each input parameter and output feature has been determined.

Algorithm 1. FNN-TLO-based dental age classification

Inputs: A test example y, a hidden feature number F, an activation function g(Cv), a training phase of m classes $Cv = [Cv_1, Cv_2, \ldots, Cv_m]$, and

Output: choosing features for cv prediction

1. The w_i, b_i Hidden feature parameters are created at random.
2. Set k=5
3. $f(Cv), Cv = (Cv_1, Cv_2, \ldots, Cv_d)$ in the objective function, where d is the definition of the design variables
4. At first, each aspect of the classroom's weights was randomly created.
5. Determined the weights of the classroom's objective function, or f(Cv), for all of the pupils (i.e., each

feature)

6. While (the termination requirements are not satisfied)
7. Do the calculation for the teaching factor and the best solution for teachers is identified.
8. For $i = 1 \to n$
9. A calculation of the teaching factor is made
10. Adapted the answer in light of the instructor's recommended course of action
11. We have computed the fitness function for the newly mapped student, which is denoted by f(Cv_{new}).
12. When Cv_{new} If X is superior to Cv, then Cv_{new}.
13. Put a stop to the "teacher phase."
14. { pupil stage }
15. Randomly chosen a different student Cv^j, so that $j \neq i$
16. If Cv^i is superior to Cv^j, then $f(Cv^i) < f(Cv^j)$ is true.
17. $Cv^i_{new} = Cv^i + rand(0,1)(Cv^i - Cv^j)$
18. Else
19. $Cv^i_{new} = Cv^i + rand(0,1)(Cv^j - Cv^i)$
20. End if
21. If Cv^i_{new} is superior to Cv, then $f(Cv^i_{new}) < f(Cv^i)$
22. $Cv^i = Cv^i_{new}$
23. Terminate if the "student phase" is complete
24. End for
25. Undertake k=k+1
26. End while
27. High-ranking characteristics are chosen

FNN classifier for Cv prediction

The chosen features are converted into an input feature for the FNN. An FNN comprises four layers [37, 38] of capacity that prepare the features needed to categorize an individual's age.

1. The input for NNs is the first layer, consisting of just the characteristics that feed into the next layer (per the spiral assumption).

2. An additional secret layer is formed by fuzzified, which takes each input value and runs it through a fuzzy membership value for a linguistic inconstant to get a fuzzy truth for that value. This layer is used to generate fuzzy rule precursors, for example.

3. A rule layer, which comes in third, deduces a future fuzzy variable from certain fuzzifying characteristics in this layer.

4. The prepared last layer is defuzzification.

Just two upgraded instances of classes, such as matched (i.e., accurate) features and non-matched (i.e., erroneous) features, are used in FNN. The FNN preparation procedure has been compared to two classes. In the information tests, the proposed framework contains N number of characteristics. Here, the two classifications are present to prepare case information$\{(Cv^{(q)}, t^{(q)}): q = 1, \dots, Q\}$,, i.e., the $t^{(q)}$ Has two labels. Additionally, the projected outline makes use of K=2 likek_1, k_2class congregations of hidden features, its functionalities communicate to a Gaussian storage norm with a corresponding label. Each Gaussian in a group has a different emphasis within a common label. Fig. 2 shows what is regarded as the class 1 primary gathering characteristic.

Whichever feature is close to another in this technique denotes that the features are combined under the same label. Gaussians performs of features are provided by two types depending on the number of foci. Then, the fuzzy truth of informational feature Cv is supplied using the Gaussian Fuzzy Based Switched Median Filter (FSMF) and is described as being in the same class as $Cv^{(q)}$.

$$Cv \to g\left(Cv, Cv^{(q)}\right) = exp\{-\left\|Cv - xCv^{(q)}\right\|^2/(2D^2 \quad (7)$$

Where $D \to$ the average distance between completely features.

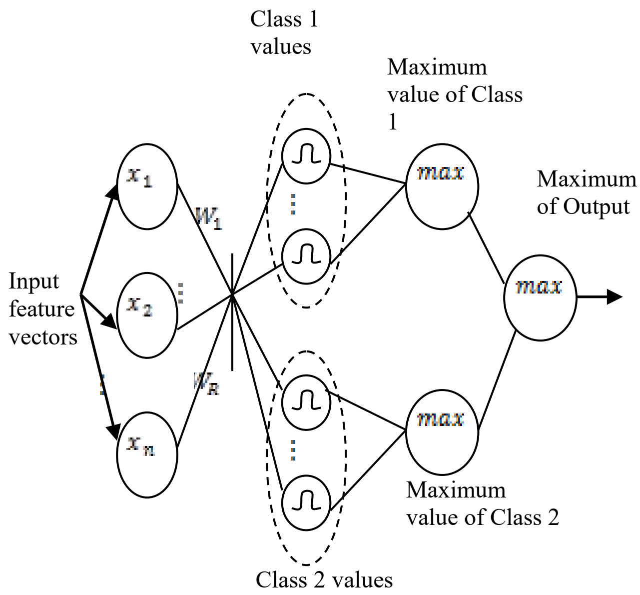

Figure 2. Architecture diagram of FNN

The full fuzzy facts for the class 1 Gaussian centers are shown in Fig. 2. class 1 is fed by the features in their Gaussian input, and the most prominent feature is chosen as fuzzy facts. They are acting in the role of a fuzzy or imprecise fact while selecting the class. For Class 1, the Cv represents a few inputs $Cv^{(k)}$. The final result maximizes the feature of the picture with the highest fuzzy reality of class 1 for x. Moreover, the final classification output is sent with the greatest fuzzy reality of class 2 for Cv. As a result, the input Cv is passed on to the output class, and the product's label is established using the Gaussian center vector. The FNN technique works as follows:

Step 1: the input parameters are initially read, which includes the feature count (N), the feature vector count (Qv), the class count (K), and the label dimension (J).

Step 2: The smallest possible distance (Md) between every pair of feature vectors is determined.

Describes F = $Md/2$

Gc = Qv expressed as the initial number of Gaussian centers, or Gc.

Step 3: generated vectors of Md with indices k 1 and k 2 for dual classes detached by d

If $d < (½)Md$ and have the same label like $\text{label}[k_1] = \text{label}[k_2]$

Then Gaussian center of $k2$ is eliminated

$Gc = Gc - 1$

Forward to Step 3 processes

Step 4: The following conditions can be used to categorize FNN unsupervised learning Cv once step 3 of the procedure is complete.

For k = 1 to Gc, do

Calculated

$$g[k] = exp\left\{-\frac{\left\|Cv - Cv^{(k)}\right\|^2}{2\sigma^2}\right\} \quad (8)$$

Founded Maximum $g[k^*]$, over k = 1... Gc

The highest output Cv, $label[k^*]$Founded, where k^* Denotes the class of Cv.

Step 5: After all inputs have been predicted, the function is complete.

4. RESULTS AND DISCUSSION

The worth of the soil's coefficient of merging may be calculated using other soil index factors thanks to a machine learning model called FNN-TLO. To simulate the coefficient, the model was used to analyze 164 soil samples. RMSE, MAE, and r were castoff to assess the model's presentation.

$$RMSE=\sqrt{\sum_{pi}^{n}\frac{\left(y_{pi}-m_{pi}\right)^2}{n}} \quad (9)$$

$$\text{MSE}=\frac{1}{n}\sum_{pi}^{n}\left|y_{pi}-m_{pi}\right| \quad (10)$$

$$\text{r}=\frac{\sum_{pi}^{n}(y_{pi}-\bar{y})(m_{pi}-\bar{m})}{\sqrt{\sum_{pi}^{n}(y_{pi}-\bar{y})^2(m_{pi}-\bar{m})^2}} \quad (11)$$

Where y_{pi} Is the value anticipated by the obtained models for the pi th sample, $\bar{y}_{pi}$ is the mean value predicted by the models, m_{pi} *and* $\bar{m}$ Is the value measured for the pith sample, and n refers to the total amount of samples. The model's effectiveness is higher the lesser the RMSE and MAE. The Cv lies in the range of 1.0 to +1.0. A perfect significant negative relationship is signified by a correlation of 1.0, and a faultless high association is represented by a correlation of 1.0. Zero or no link between the actions of the 2 factors is indicated by a correlation of 0.0.

The evaluation of suggested and current approaches for RMSE is shown in Fig. 3. Due to the high effectiveness of feature extraction and fuzzy assessment of Cv, the suggested FNN-TLO achieved smaller RMSE and MSE when compared to current MLP-BBO, SVR, and Bp-MLP Neural Nets. The suggested achieved RMSE is 0.37 fewer errors in Fig 3 compared to the outgoing MLP-BBO (0.387), SVR (0.429), and Bp-MLP Neural Nets (0.484).

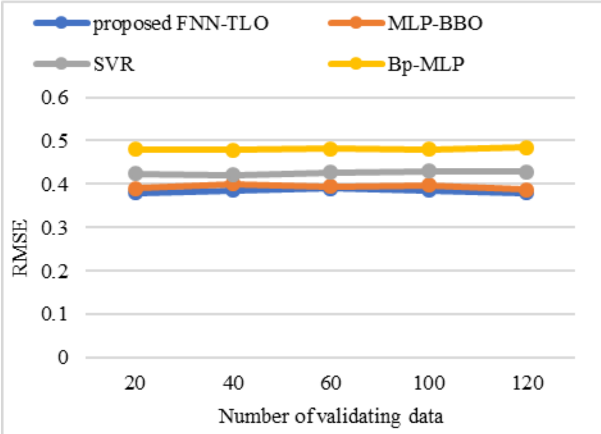

Figure 3. RMSE Comparison Results between Existing and Proposed Methods

The MSE of the suggested achieved 0.26 fewer errors in comparison to the outgoing MLP-BBO (0.269), SVR (0.302), and Bp-MLP Neural Nets, as shown in Fig. 4. (0.322). The MSE of the suggested system achieved lower error thanks to the effective feature selection and fuzzy selection.

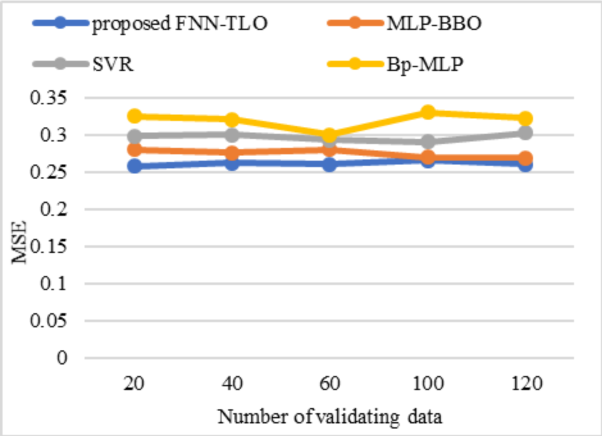

Figure 4. MSE Comparison Results between Existing and Proposed Methods

The assessment results of the suggested and current approaches' correlation coefficients (r) are shown in Fig. 5. Due to the effective fuzzy prediction. It can be shown that the suggested FNN-TLO achieved high (r) compared to current MLP-BBO, SVR, and Bp-MLP Neural Nets. Compared to the existing MLP-BBO (0.827), SVR (0.819), and Bp-MLP Neural Nets, the suggested FNN-TLO achieved a high coefficient of 0.835. (0.804).

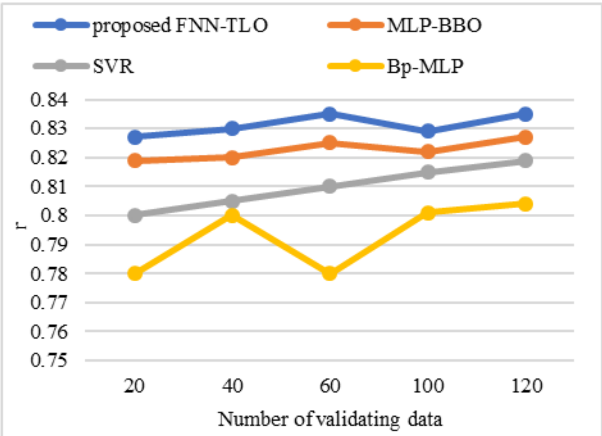

Figure 5. MSE Comparison Results between Existing and Proposed Methods

5. CONCLUSION

Several approaches were utilized in the previous to calculate Cv. Yet, as new technologies have evolved, it is now vital to review the effectiveness of present models and build different, more successful ones. Specifically for predicting soil Cv, the FNN-TLO algorithm was created. The proposed FNN-TLO model outperforms comparable models such as the MLP-BBO, the SVR, and the Bp-MLP Neural Nets. The FNN-TLO model had the best r-value, smallest RMSE (0.379), and second-smallest MAE (0.26). (0.835). Consequently, it can be deduced that the recommended model (FNN-TLO) can be applied to provide superior Cv value forecasting, which can subsequently be used for optimum gradient and beginning of the planning process.

However, it should be noted that the success of this methodology is based on research into information from only two highway construction projects. For this reason, verifying the proposed model's forecasts of the Cv readings at other projects aimed may also necessitate a few field or laboratory investigations for various soil types. For the most accurate Cv prediction, it is recommended that future studies investigate neural networks with strong links and other deep learning optimization techniques.

References

[1] Narasimha P, Pandian N, Nagaraj T. Analysis and estimation of the coefficient of consolidation. Geotechnical Testing Journal .1995;Vol. 18 (2):pp. 252–258.

[2] Shahin M A, Jaksa M B, Maier H R. Recent advances and future challenges for artificial neural systems in geotechnical engineering applications. Advanced Artificial Neural System.2009; pp. 5.

[3] Schnaid F, Sills G C, Soares, Nyirenda Z. Predictions of the coefficient of consolidation from piezocone tests. Canadian Geotechnology Journal. 1997; Vol. 34 (2):pp. 315–327.

[4] Sivakugan N, Eckersley J, Li H. Settlement predictions using neural networks. Australian Civil Engineering Transaction. 1998; Vol. 40: pp. 49–52.

[5] Ryohei I, Noriyuki Y, Michael J. An estimation method for predicting final consolidation settlement of ground improved by floating soil cement columns. Soils Foundation. 2016; Vol. 56 (2): pp. 213–227.

[6] Chen W M, Panahi M, Pourghasemi H R. Performance evaluation of GIS-based new ensemble data mining techniques of adaptive neuro-fuzzy inference system (ANFIS) with genetic algorithm (GA), differential evolution (DE), and particle swarm optimization (PSO) for landslide spatial modelling. CATENA.2017; pp. 310–324.

[7] Gooroochurn M, Kerr D, Bouazza-Marouf K. A machine learning approach to tracking and characterizing planar or near planar fluid flow, International Journal Natural Computer Research (IJNCR).2020; Vol. 9 (3):pp. 76–87.

[8] Johari A, Javadi A, Habibagahi G.: Modelling the mechanical behavior of unsaturated soils using a genetic algorithm-based neural network. Computer Geotechnics. 2011; Vol. 38 (1):pp. 2–13.

[9] Kaya A. Residual and fully softened strength evaluation of soils using artificial neural networks. Geotechnical Geological Engineering.2009; Vol. 27 (2):pp. 281–288.

[10] Pham B T, Son L H, Hoang T A, Nguyen D M, Bui D T. Prediction of shear strength of soft soil using machine learning methods. CATENA.2018; Vol. 166: pp. 181–191.

[11] Thai B, Sushant K, Hai-Bang Ly. Using Artificial Neural Network for prediction of soil coefficient of consolidation. Vietnam Journal Earth Science. 2020; Vol.42 (4).

[12] Manh Duc Nguyen, Binh Thai Pham, Lanh Si Ho.: Soft-computing techniques for prediction of soils consolidation coefficient, CATENA. Vol. 195 (2020).

[13] Sathya Ramasamy, Ananthi Selvarajan, Vaidehi Kaliyaperumal, Prasanth Aruchamy. A hybrid location-dependent ultra-convolutional neural network-based vehicle number plate recognition approach for intelligent transportation systems. Concurrency and Computation. Practice and Experience. 2023; Vol. 35(1).

[14] Verleysen M, François D. The curse of dimensionality in data mining and time series prediction. Computational Intelligence and Bioinspired Systems, Springer Berlin Heidelberg, Berlin, Heidelberg, 2005; pp. 758–770.

[15] Sridharan A, Nagaraj H. Coefficient of consolidation and its correlation with index properties of remolded soils. Geotech. Test. Journal.2004; Vol.27: pp.469–474.

[16] Chen W. Landslide susceptibility modelling using GIS-based machine learning techniques for Chongren County, Jiangxi Province, China Science Total Environmental. 2018; Vol. 626: pp. 1121–1135.

[17] Chen W. A novel hybrid artificial intelligence approach based on the rotation forest ensemble and naïve Bayes tree classifiers for a landslide susceptibility assessment in Langao County, China. Geomatics Natural Hazard Risk. 2018; Vol.8: pp. 1955–1977.

[18] Chen W. GIS-based landslide susceptibility evaluation using a novel hybrid integration approach of bivariate statistical based random forest method. Catena.2018; Vol.164: pp. 135–149.

[19] Chen W.: GIS-based landslide susceptibility modelling: a comparative assessment of kernel logistic regression, Naïve Bayes tree, and alternating decision tree models Geomatics Natural Hazard Risk. 2017; Vol.8: pp. 950–973.

[20] Pham B T, Prakash I. Evaluation and comparison of LogitBoost Ensemble, Fisher's Linear Discriminant Analysis, logistic regression, and support vector machines methods for landslide susceptibility mapping. Geocarto International. 2017; pp.1–32.

[21] Qi C, Tang X. Slope stability prediction using integrated metaheuristic and machine learning approaches: a comparative study. Computer International Engineering. 2018; Vol. 118: pp.112–122.

[22] Shahabi H, Hashim M. Landslide susceptibility mapping using GIS-based statistical models and remote sensing data in tropical environment. Scientific Reports.2015; Vol.5 .

[23] Shadman Roodposhti M, Aryal J, Shahabi H, Safarrad T. Fuzzy Shannon entropy: a hybrid GIS-based landslide susceptibility mapping method. Entropy. 2016; Vol. 18: pp. 343.

[24] Kanungo D P, Sharma S, Pain A. Artificial neural network and regression tree (CART) applications for the indirect estimation of unsaturated soil shear strength parameters. Frontiers of Earth Science. 2014; Vol. 8: pp. 439–456.

[25] Niranjani V, Selvam N S. Overview on Deep Neural Networks: Architecture, Application and Rising Analysis Trends. EAI/Springer Innovations in Communication and Computing. 2020; pp. 271–278.

[26] Kiran S, Lal B, Tripathy S.Shear strength prediction of soil based on probabilistic neural network. Indian Journal Science and Technology. Vol. 9.

[27] Erzin Y, Ecemis N. The use of neural networks for the prediction of cone penetration resistance of silty sands. Neural Computing. & Application. 2017; Vol. 28: pp.727–736.

[28] Javdanian H, Lee S. Evaluating unconfined compressive strength of cohesive soils stabilized with geopolymer: a computational intelligence approach. Engineering with Computers. pp. 1–9.

[29] Pham B T, Nguyen M D, Bui K. A novel artificial intelligence approach based on Multi-layer Perceptron Neural Network and Biogeography-based Optimization for predicting coefficient of consolidation of soil. Catena. 2019; Vol. 173: pp. 302-311.

[30] Mittal, Mamta, Suresh Chandra Satapathy. Prediction of coefficient of consolidation in soil using machine learning techniques. Microprocessors and Microsystems. 2021; Vol.82.

[31] Das B M, Sobhan K. Principles of Geotechnical Engineering. Cengage learning. 2013.

[32] Spagnoli G, Feinendegen M.: Relationship between measured plastic boundary and plastic boundary estimated from undrained shear strength, water content ratio and liquidity index. Clay Miner. 2017: Vol.52: pp. 509–519.

[33] Kihara E N, Gichangi P, Liversidge H M, Butt F.: Dental age estimation in a group of Kenyan children using Willems' method: a radiographic study. Annals of Human Biology. 2017; pp. 1-8.

[34] Crespinsek M, Liu S H, Mernik L. A note on teaching-learning-based optimization algorithm. Information Sciences. 2012; Vol. 212: pp. 79-93.

[35] Rao R V, Savsani V J, Vakharia D P. Teaching-learning-based optimization: An optimization method for continuous nonlinear large scale problems. Information Sciences. 2012; Vol. 183: pp. 1-15.

[36] Gabrys B, Burgiela A. General fuzzy min-max neural network for clustering and classification. IEEE Transactions Neural Networks. 2000; Vol. 11(3): pp. 769-783.

[37] Lee H M, Chen C M, Jou Y L: An efficient fuzzy classifier with feature selection based on fuzzy entropy. IEEE Transactions SMC-B. 2001; Vol. 31(3): pp. 426-432.