ISSN Online: 2821-1693

Transactions on Machine Intelligence

Journal Homepage: https://tmachineintelligence.ir/

Modeling the Impact of Soil Liquefaction on Structural Stability Using an Artificial Neural Network Optimized by the Cuckoo Optimization Algorithm

M. Foroutan Naddafi [1,*]

[1] Department of Civil Engineering and Architecture, National University of Skills, Tehran, Iran.

ARTICLE INFO

Article History:
Received 3 March 2025
Received in revised form 17 June 2025
Accepted 10 August 2025
Available online 1 September 2025

Keywords:
Soil liquefaction, Structural stability, Artificial Neural Network, Cuckoo Optimization Algorithm.

ABSTRACT

Soil liquefaction is one of the most critical geotechnical phenomena that can severely impact the stability and performance of engineering structures during seismic events. Accurate prediction of liquefaction potential and its subsequent effects on structural stability is a complex, non-linear problem influenced by a combination of intertwined geotechnical and seismic parameters. In this research, an Artificial Neural Network (ANN) model was developed to simulate and predict the impact of soil liquefaction on structural stability using a comprehensive dataset of geotechnical and seismic features. To enhance the predictive performance and generalization capability of the neural network, the hyperparameters and network architecture were optimized using the Cuckoo Optimization Algorithm (COA) an algorithm that enables the simultaneous optimization of multiple conflicting objectives, such as prediction accuracy and model complexity. The optimized neural network demonstrated highly superior performance in classifying liquefaction and non-liquefaction states, delivering high accuracy and remarkable stability on the validation dataset. Furthermore, the hybrid ANN–COA framework provides a reliable, efficient, and computational approach for assessing the impact of liquefaction on structural stability, offering valuable insights for seismic design, risk assessment, and the formulation of hazard mitigation strategies in geotechnical engineering.

1. INTRODUCTION

Soil liquefaction is one of the most complex and destructive phenomena in geotechnical engineering, occurring during severe earthquakes in loose, saturated sandy, silty, or granular soils. Under such conditions, the rise in excess pore water pressure leads to a reduction in the effective stress of the soil, resulting in a complete loss of its shear strength. Consequently, the soil loses its bearing capacity and behaves like a liquid. This phenomenon can cause sudden settlement, tilting, or even the catastrophic collapse of structures built upon such deposits. Historical earthquakes, such as the 1964 Niigata earthquake and the 1995 Kobe earthquake, have clearly demonstrated the devastating effects of liquefaction on buildings and infrastructure. Therefore, understanding the mechanism of liquefaction and accurately modeling its impact on soil-structure interaction is essential for seismic safety assessment and resilient geotechnical design [1-2].

* Corresponding Author: mforoutannaddafi@tvu.ac.ir
Department of Civil Engineering and Architecture, National University of Skills, Tehran, Iran

https://doi.org/10.22034/tmi.2025.244855

The significance of modeling the impact of soil liquefaction on structural stability lies in its direct effect on the performance and bearing capacity of foundations, retaining walls, bridges, and buried pipelines. When the soil beneath a foundation liquefies during an earthquake, the stress contact between the soil and the structure is lost, triggering abrupt load redistribution and deformations. These events can lead to excessive settlement, tilting, or total structural failure. From a seismic design perspective, neglecting liquefaction effects in stability analysis can result in an underestimation of safety margins and lead to unsafe designs. Thus, accurate liquefaction modeling is vital for risk assessment, design optimization, and the development of engineering codes and standards. Through reliable modeling, engineers can identify vulnerable zones, select appropriate foundation types, and predict structural response under severe seismic conditions [3-5].

The application of liquefaction modeling extends beyond hazard prediction into various domains of geotechnical and structural engineering. Analytical, numerical, and data-driven models allow engineers to estimate settlements, lateral displacements, and post-liquefaction stiffness degradation of soil layers, which are critical for soil improvement and foundation design. Furthermore, modeling evaluates the impact of key parameters such as soil density, fine content, groundwater level, and seismic intensity on liquefaction potential. This approach is of particular importance in coastal regions, ports, and cities where critical infrastructure is constructed on soft, saturated deposits. In addition, data-driven models can assist in generating liquefaction hazard maps and developing early warning systems, thereby contributing to the mitigation of human and economic losses in future earthquakes [6-7].

Despite recent advancements, modeling liquefaction remains a significant challenge. Traditional empirical relationships are valid only for specific site conditions and fail to fully capture the complex, non-linear interactions among soil parameters. Numerical models, while providing detailed physical insights, require deterministic soil parameters that can only be obtained through expensive and time-consuming laboratory testing. Moreover, many regions lack sufficient field data, such as Standard Penetration Test (SPT) or Cone Penetration Test (CPT) results, which limits model reliability. Liquefaction is inherently a stochastic phenomenon, making its prediction difficult using deterministic analytical methods. These limitations highlight the urgent need for intelligent, data-driven approaches capable of handling uncertainty and complexity.

In recent years, Artificial Neural Networks (ANNs) have emerged as powerful tools for modeling the non-linear, multivariate relationships associated with soil liquefaction. Inspired by the human brain, neural networks can learn complex dependencies between input variables without requiring an explicit mathematical formulation. Once trained on actual field data, these networks can predict the probability of liquefaction occurrence and its subsequent effect on structural stability with high accuracy. Their advantages include adaptability to new data, high predictive precision, and minimal reliance on physical model assumptions. Furthermore, hybrid methods that combine neural networks with metaheuristic optimization algorithms, such as the Cuckoo Optimization Algorithm (COA), have significantly enhanced model accuracy and convergence rates. Overall, the application of ANNs offers a modern and efficient approach for predicting soil behavior under liquefaction conditions and assessing the seismic resilience of structures.

The remainder of this paper is structured as follows: Section 2 reviews existing methods in soil liquefaction modeling. Section 3 introduces the proposed methodology based on the Artificial Neural Network optimized by the Cuckoo Optimization Algorithm. Section 4 presents the simulation results and evaluates the model's performance, and Section 5 is dedicated to the summary and conclusions.

2. EXISTING METHODS

Liquefaction is considered one of the most serious hazards affecting granular soils. This phenomenon primarily occurs when loose soil is subjected to dynamic loading or seismic activity. In study [1], the liquefaction of loose soil was evaluated and specific recommendations were provided. A two-dimensional numerical analysis was conducted to simulate the behavior of loose soil under dynamic loads. The analyzed model consisted of a multi-layered soil deposit reinforced with stone columns subjected to dynamic loading. It was observed that stone columns improve soil behavior and mitigate liquefaction-induced damage. Additionally, increasing the shear parameters of the soil can restrict liquefaction. Since damage resulting from dynamic loading is time-dependent, longer durations of applied load lead to increased damage. In that research, various tensile effects were investigated, and a comparative study encompassing excess pore water pressure, total vertical settlement, soil deformation, and soil velocity was presented.

Liquefaction leads to a reduction in soil strength and stiffness due to seismic or dynamic effects, causing substantial damage in global earthquakes. Soil behavior is modeled to predict liquefaction, and among the available models, the UBC3D-PLM model has been utilized for this purpose. In study [2], the capabilities of this model were investigated by simulating the seismic effects on buildings of various heights using PLAXIS software. Data from the 1990 Upland earthquake near Los Angeles were employed. The results revealed a significant discrepancy between actual soil behavior and elastic assumptions, highlighting the necessity of utilizing the UBC3D-PLM model in seismic assessments.

Recent methods for measuring and preventing soil liquefaction were reviewed in study [3]. Tests such as the Standard Penetration Test (SPT), Cone Penetration Test (CPT), shear wave velocity, cyclic simple shear, and triaxial tests are utilized to evaluate liquefaction potential. Soil improvement techniques, including compaction, vibro-compaction, deep soil mixing, and reinforcement, are implemented to mitigate the risk. Advanced numerical modeling and artificial intelligence have also been deployed for prediction. Adherence to seismic design codes, zoning regulations, and community education are recommended to reduce liquefaction impacts. These methods establish a foundation for developing resilient infrastructure in seismically active regions.

The impact of soil liquefaction on pile-supported buildings was investigated in study [4]. Structural responses and potential consequences during the temporary loss of soil strength during an earthquake were analyzed. To mitigate risk, detailed site investigations, soil improvement techniques, and rigorous engineering design are recommended. This study provides insights into enhancing structural stability and supporting the design of resilient buildings in liquefaction-prone areas.

The efficiency of pile foundations for offshore facilities, particularly floating wind turbines, was evaluated using advanced liquefaction modeling [5]. Non-linear analyses were performed using FLAC3D and the SANISAND model, which is capable of simulating pore pressure generation. The results indicate that lateral displacement and tilting of piles can occur due to the combined effects of seismic shaking and static loads induced by liquefaction.

In study [6], the liquefaction response of railway embankments on fine-grained soils was predicted using an Advanced Machine Learning (EML) approach based on ANNs, ANFIS, and metaheuristic optimization. Machine learning techniques were applied for multivariate non-linear approximations. Ten EML models were evaluated, and the results demonstrated high accuracy in predicting the factor of safety against liquefaction. The ANFIS-FF model was the most successful, yielding R^2 values of 91% and 85% for the training and testing datasets, respectively. The findings indicate that the ANFIS-based EML model is more reliable than existing methods for predicting liquefaction development and assessing the dynamic behavior of railway embankments on fine-grained soils.

In research [7], the Bayesian inference method was employed for probabilistic modeling using a comprehensive SPT database. For the first time, the First-Order Reliability Method (FORM) and importance sampling were used to estimate the failure probability and the reliability index of the liquefaction limit state function.

To enhance predictive accuracy, a hybrid ensemble learning model with Bayesian Optimization (BO-stacking) was introduced [8]. Primary algorithms included Decision Tree, Support Vector Machine, and k-Nearest Neighbors, combined with Random Forest as the secondary meta-learner, while Bayesian optimization was applied for hyperparameter tuning. Input selection was performed using the mutual information technique. The results showed that BO-stacking outperforms single predictive models, achieving a test accuracy of 0.913 and an AUC of 0.992. This study demonstrates that combining BO and stacking is a reliable method for soil liquefaction prediction.

Several other methods are also available. The KNN method is used for non-linear regression and offers high predictive accuracy due to its robustness against outliers [9]. The Decision Tree algorithm provides high computational speed and can generate practical, data-driven results within a short timeframe [10]. Under conditions of limited training data, SVM exhibits superior performance because it delivers strong generalization capability and effective information retention [11].

3. PROPOSED METHODOLOGY

In this study, a feedforward Artificial Neural Network (ANN) is employed to model the impact of soil liquefaction on structural stability (Figure 1). Due to its high capability in approximating non-linear functions and learning complex relationships between input and output variables, this type of network is considered one of the most powerful tools in geotechnical analyses [5-8]. The general architecture of the network consists of an input layer that receives geotechnical and seismic parameters such as groundwater depth, Vs30, SPT, PGA, and CPT; two hidden layers with Rectified Linear Unit (ReLU) activation functions to enhance the non-linear recognition capability; and an output layer based on the softmax function, which determines the probability of liquefaction occurrence or non-occurrence. Consequently, the network is capable of classifying multidimensional data into two classes, providing more accurate predictions compared to traditional statistical methods.

3.1. Structural Hyperparameters

In the design of an artificial neural network, several parameters significantly influence the final performance of the model. These parameters, known as structural hyperparameters, include the number of neurons in each layer, the number of hidden layers, the types of activation functions, and the connectivity pattern between layers. In the present network, the number of neurons in the initial hidden layers (32 and 16 neurons) is treated as a variable so that the optimal combination of these parameters can be obtained via an optimization algorithm. Proper selection of the number of neurons directly affects the learning capacity of the network, the convergence speed, and the prevention of overfitting. Moreover, the type of activation function whether ReLU, tanh, or sigmoid can influence the non-linear behavior of the network and the manner in which signals are processed.

3.2. Multi-Objective Optimization

In this study, two primary objectives are defined for neural network optimization to enhance the model's performance in terms of accuracy and efficiency. The first objective is to increase the classification accuracy of the model, enabling the neural network to effectively learn the complex relationships between input features and output classes, thereby correctly classifying samples into liquefaction or non-liquefaction states. Metrics such as Accuracy and Precision are used for the quantitative evaluation of the model's predictive performance.

The second objective is to minimize model complexity, which is measured in this study by the network training time. This objective is crucial in engineering applications, as reducing training time not only saves computational resources but also enables faster deployment of the model in real-world scenarios. Furthermore, a short training time is typically associated with simpler models, which helps mitigate overfitting and improves the generalization capability of the network.

Given these two objectives, the problem is formulated as a multi-objective optimization task. The aim of this approach is to find an optimal trade-off between high accuracy and short training time, as excessively increasing accuracy can lead to higher complexity and prolonged training periods, and vice versa. Multi-objective algorithms, such as the Cuckoo Optimization Algorithm, enable the generation of a set of optimal models with varying levels of balance (Pareto-optimal front). From these, researchers can select the model that best suits the specific requirements of the project [12].

3.3. Proposed Framework

The overall procedure of the proposed methodology for modeling the impact of soil liquefaction on structural stability using an artificial neural network optimized by the Cuckoo Optimization Algorithm is described below as a continuous workflow (Figure 1):

First, geotechnical and seismic data, including groundwater depth, shear wave velocity (Vs30), SPT and CPT results, peak ground acceleration (PGA), and other relevant parameters, are collected. To mitigate the effects of varying scales, these data are normalized using methods such as Min-Max scaling or Z-score normalization, and are subsequently partitioned into training, validation, and testing datasets.

In the next step, the artificial neural network is designed. The network architecture comprises an input layer to receive the parameters, two or more hidden layers with non-linear activation functions such as ReLU, and an output layer with a softmax function for binary classification (liquefaction/non-liquefaction). At this stage, the structural hyperparameters of the network, including the number of neurons, the number of hidden layers, and the type of activation function, are initialized.

The optimization objectives of the network encompass two main aspects. The first objective is to maximize the predictive accuracy of the network in classifying samples into liquefaction or non-liquefaction states, evaluated using metrics such as Accuracy and Precision. The second objective is to reduce network complexity, typically measured by training time, which suppresses overfitting and enhances the model's generalization capability.

To find the optimal combination of hyperparameters, the Cuckoo Optimization Algorithm (COA) is employed. First, the search space for the parameters is defined, and each network configuration is considered an individual within the algorithm's population. The networks are constructed and trained based on their respective specifications, and their performance metrics are fed back to the algorithm as objective functions. New generations are produced using the algorithm's operators to optimize the model and prevent premature convergence.

Upon completion of the optimization process, a model that offers the best balance between high accuracy and low complexity is selected from the set of optimal models. The final model is evaluated on the testing dataset to measure its actual performance in predicting soil liquefaction and its impact on structural stability.

Ultimately, this model is deployed to predict the occurrence of liquefaction and its consequences on structures, thereby assisting engineers in seismic design and geotechnical engineering planning in liquefaction-prone regions.

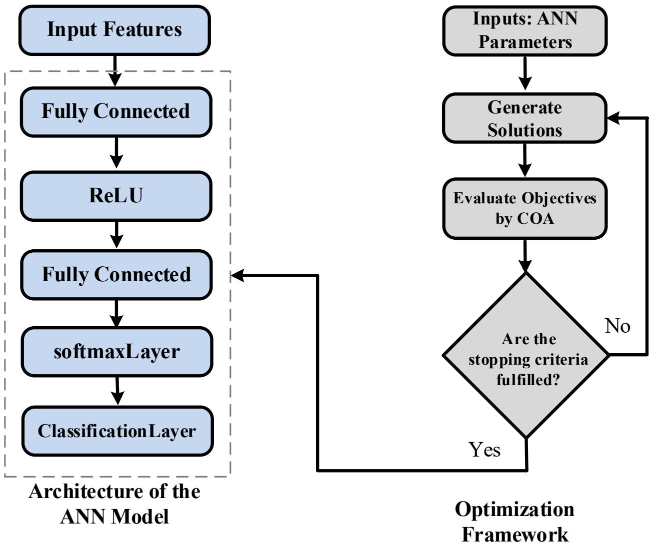

Fig. 1. Flowchart of the proposed methodology.

4. SIMULATION RESULTS

The proposed methodology and the alternative baseline methods were implemented using MATLAB software, developed by MathWorks. The hardware configuration utilized for the simulations consisted of an Intel(R) Core™ i5-4460 CPU @ 3.2 GHz processor with 16 GB of RAM.

The Next Generation Liquefaction (NGL) project is an international collaborative research initiative in geotechnical engineering aimed at collecting and standardizing soil liquefaction data, as well as developing probabilistic models to predict its occurrence and consequences. This project provides a global, open-access database of liquefaction case histories, encompassing diverse sites, seismic events, and post-earthquake field observations. The database includes carefully validated case histories of both liquefaction and non-liquefaction occurrences. Based on these data, advanced probabilistic models have been developed to predict the likelihood and severity of liquefaction using geotechnical and seismic parameters. These models enable engineers to perform liquefaction hazard analyses with higher precision and reliability, facilitating resilient seismic design and critical infrastructure planning, while also serving as a benchmark reference for future model development [13].

To ensure a fair and reliable evaluation process, the dataset was systematically partitioned into three independent subsets. Seventy percent (70%) of the data was allocated for model training to learn the underlying patterns, while fifteen percent (15%) was dedicated to validation for hyperparameter tuning and monitoring the learning process. The remaining fifteen percent (15%) was strictly reserved for testing to evaluate the final performance of the model on entirely unseen data. This data-splitting strategy maintains objectivity during the evaluation phase, prevents data leakage between the training and testing stages, and enhances the reliability of the empirical findings.

During the training of the proposed neural network, the model's performance was monitored over successive epochs. As the number of training iterations increased, the model's accuracy progressively improved, and the loss function continuously decreased, indicating effective learning by the network. This trend confirms that the network converges correctly and minimizes prediction errors. Figure 2 illustrates the training curves, where the ascending trend of accuracy and the descending trend of the loss function are clearly visible. These results demonstrate that the selected network architecture and the hyperparameters optimized by the Cuckoo Optimization Algorithm (COA) enable efficient feature learning from the input data without suffering from premature overfitting.

To evaluate final performance, the proposed method was compared against several widely used machine learning approaches, including KNN [9], Decision Tree [10], SVM [11], and Stacking [8]. Based on the obtained results, the proposed model demonstrated the highest performance, achieving an outstanding accuracy of approximately 99.8% along with superior precision, whereas the best-performing competing method (Stacking) reached an accuracy of 99.2%. Methods such as KNN and SVM exhibited lower performance, and while the Decision Tree offered acceptable accuracy, it still underperformed compared to the proposed approach. These comparisons demonstrate that the proposed method significantly outperforms existing techniques in terms of both accuracy and precision.

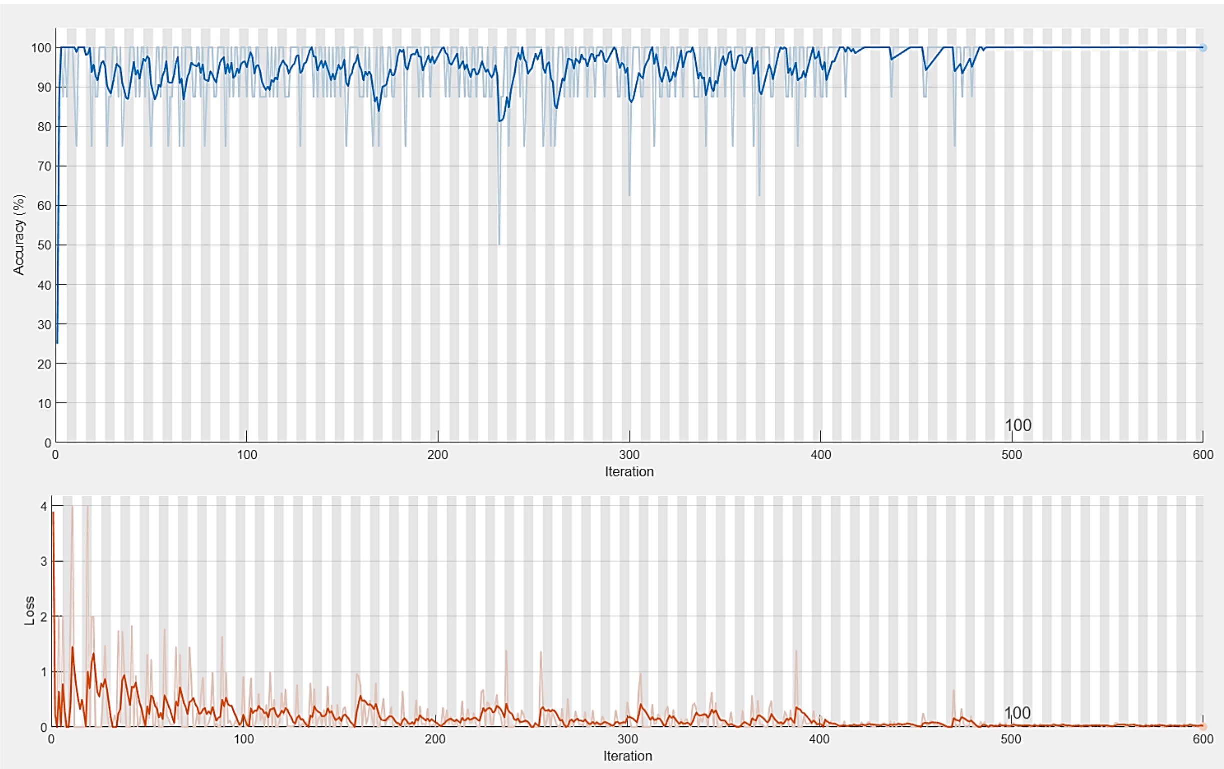

Fig. 2. Training performance of the proposed neural network, illustrating the increase in accuracy and the decrease in the loss function over successive epochs.

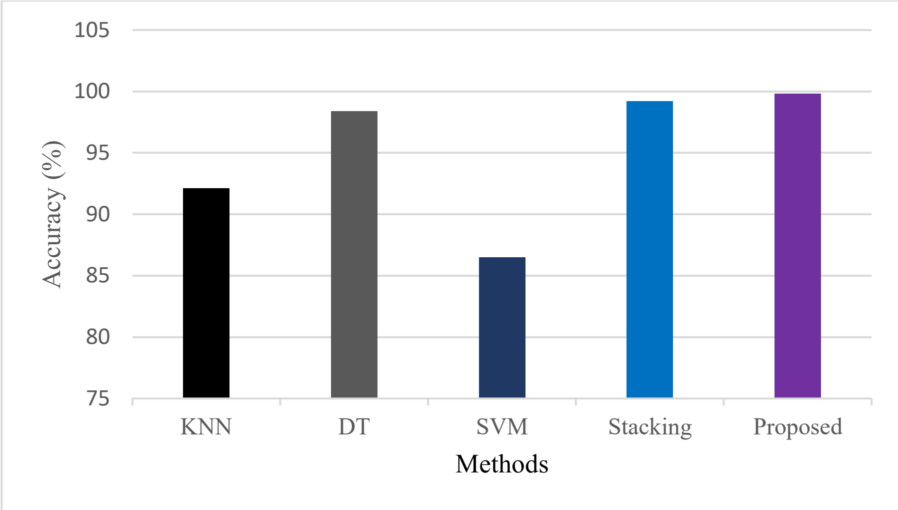

Fig. 3. Comparative analysis of model accuracy between the proposed method and existing methods.

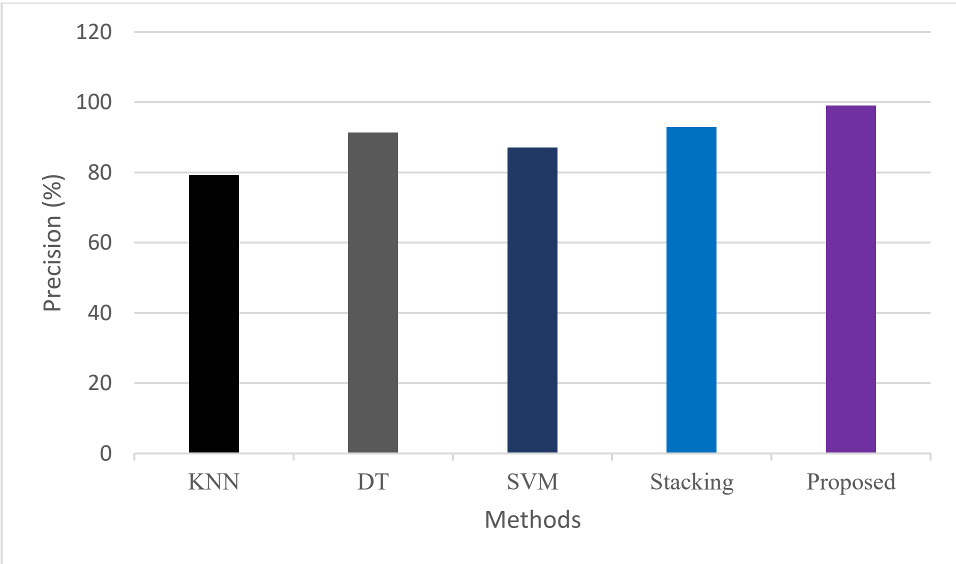

Fig. 4. Comparative analysis of model precision between the proposed method and existing methods.

5. CONCLUSION

In this study, a feedforward neural network was integrated with a multi-objective optimization framework based on the Cuckoo Optimization Algorithm (COA) to model the impact of soil liquefaction on structural stability. Aiming to maximize classification accuracy while simultaneously minimizing model complexity and training time, this approach systematically evaluated and optimized various combinations of network architectures and hyperparameters.

The experimental results demonstrated that the proposed method outperforms conventional techniques such as KNN, Decision Tree, SVM, and Stacking, achieving an outstanding accuracy of 99.8% and a high precision exceeding 98%. The framework automatically tunes the structural hyperparameters of the network based on the Pareto-optimal front, which significantly enhances predictive performance and effectively prevents overfitting. This methodology provides a systematic and robust approach for geotechnical applications involving non-linear and highvariance data, and offers strong generalization capability for extension to other predictive tasks in civil and structural engineering.

Declaration

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

Acknowledgments

We would like to express our gratitude to all individuals who contributed to this project.

Declaration of Interest

The authors declare that they have no competing interests.

Funding

This research received no specific grant from any funding agency, commercial, or not-for-profit sectors.

REFERENCES

[1] Shahien, M., Nasr, A., & Mohamed, B. (2025). Modeling liquefaction mitigation of loose soil subjected to seismic loads supported by vertical drains. *International Journal of Advances in Structural and Geotechnical Engineering, 9*(4), 79–91. https://doi.org/10.21608/asge.2025.485255

[2] Ter-Martirosyan, A., & Othman, A. (2019). Simulation of soil liquefaction due to earthquake loading. *E3S Web of Conferences, 97*, Article 03025. https://doi.org/10.1051/e3sconf/20199703025

[3] Subha, D. D. R., Jayganesh, D., Kanthavelkumaran, N., & Pragash, M. S. (2025). Review on recent advances in soil liquefaction. *International Journal of Environmental Sciences, 11*(5), 2212–2219. https://doi.org/10.64252/bdnn0y94

[4] Rawani, A. K., & Singh, R. V. (2023). Soil liquefaction and its impact on pile foundations. *International Research Journal of Modernization in Engineering Technology and Science, 5*(10). https://doi.org/10.56726/IRJMETS45356

[5] Kazemi Esfeh, P., & Kaynia, A. M. (2019). Numerical modeling of liquefaction and its impact on anchor piles for floating offshore structures. *Soil Dynamics and Earthquake Engineering, 127*, Article 105839. https://doi.org/10.1016/j.soildyn.2019.105839

[6] Ghani, S., & Kumari, S. (2023). Prediction of soil liquefaction for railway embankment resting on fine soil deposits using enhanced machine learning techniques. *Journal of Earth System Science, 132*(3), Article 145. https://doi.org/10.1007/s12040-023-02156-4

[7] Sharafi, H., & Hassanzadeh, S. F. (2021). Assessment of liquefaction potential based on a probabilistic model and performing reliability analysis with evaluation of the relative importance of model parameters uncertainty. *Journal of Structural and Construction Engineering, 8*(Special Issue 1), 174–193. https://doi.org/10.22065/jsce.2020.205312.1973

[8] Tsang, L., Akbari, M., & Fakharian, P. (2025). Prediction of soil liquefaction using a multi-algorithm

technique: Stacking ensemble techniques and Bayesian optimization. *Journal of Soft Computing in Civil Engineering, 9*(2), 33–56. https://doi.org/10.22115/SCCE.2024.453006.1860

[9] Song, Y., Liang, J., Lu, J., & Zhao, X. (2017). An efficient instance selection algorithm for k nearest neighbor regression. *Neurocomputing, 251*, 26–34. https://doi.org/10.1016/j.neucom.2017.04.018

[10] Pekel, E. (2020). Estimation of soil moisture using decision tree regression. *Theoretical and Applied Climatology, 139*, 1111–1119. https://doi.org/10.1007/s00704-019-03048-8

[11] Jain, D. K., Dubey, S. B., Choubey, R. K., Sinhal, A., & Wang, H. (2018). An approach for hyperspectral image classification by optimizing SVM using self organizing map. *Journal of Computational Science, 25*, 252–259. https://doi.org/10.1016/j.jocs.2017.07.016

[12] Rajabioun, R. (2011). Cuckoo optimization algorithm. *Applied Soft Computing, 11*(8), 5508–5518. https://doi.org/10.1016/j.asoc.2011.05.008

[13] Next Generation Liquefaction. (n.d.). *Next Generation Liquefaction*. Retrieved 14 November 2025, from https://nextgenerationliquefaction.org/