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Modeling the Impact of Soil Liquefaction on Structural Stability Using an Artificial Neural Network Optimized by NSGA-III

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Abstract

Soil liquefaction is one of the most critical geotechnical phenomena that can severely compromise the stability and performance of engineering structures during seismic events. Accurate prediction of liquefaction potential and its subsequent effects on structural stability remains a complex and nonlinear problem influenced by multiple interdependent soil and seismic parameters. In this study, an Artificial Neural Network (ANN) model is developed to model and predict the impact of soil liquefaction on structural stability using a comprehensive set of geotechnical and seismic input features, including groundwater depth, shear wave velocity (Vs30), standard penetration test (SPT) results, and peak ground acceleration (PGA). To enhance the predictive performance and generalization capability of the ANN, its hyperparameters and network architecture are optimized through the Non-dominated Sorting Genetic Algorithm III (NSGA-III), which allows for simultaneous optimization of multiple conflicting objectives such as prediction accuracy and model complexity. The optimized ANN demonstrates superior performance in classifying liquefaction and non-liquefaction cases, achieving high accuracy and robustness across validation datasets. Moreover, the proposed hybrid NSGA-III–ANN framework provides a reliable and efficient computational approach for evaluating the influence of liquefaction on structural stability, offering valuable insights for seismic design, risk assessment, and mitigation strategies in geotechnical engineering.

Keywords: Soil liquefaction, Structural stability, Artificial Neural Network (ANN), NSGA-III optimization, Seismic analysis**.**

1. Introduction

Soil liquefaction is among the most complex and destructive phenomena in geotechnical engineering, typically occurring in saturated sandy, silty, or loose granular soils during strong earthquakes [1–3]. In such conditions, the increase in pore water pressure reduces the effective stress, resulting in a complete loss of shear strength. Consequently, the soil loses its load-bearing capacity and begins to behave like a liquid. This leads to sudden settlement, tilting, or even total collapse of structures built on 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 infrastructures. Therefore, a thorough understanding of the liquefaction mechanism and accurate modeling of its effects on soil and structural behavior are essential for seismic safety assessment and resilient geotechnical design.

The importance of modeling the effect of soil liquefaction on structural stability lies in its direct impact on the performance and bearing capacity of foundations, retaining

walls, bridges, and buried pipelines [1–3]. When the soil beneath a foundation liquefies during an earthquake, the contact stress between the soil and the structure is lost, leading to sudden redistributions of load and deformation. Such events may cause excessive settlement, tilting, or complete structural failure. From a seismic design perspective, neglecting liquefaction effects in stability analysis may result in underestimated safety factors and unsafe structural designs. Therefore, accurate modeling of soil liquefaction is crucial for hazard assessment, design optimization, and the development of engineering codes and standards. Reliable modeling enables engineers to identify susceptible areas, select appropriate foundation types, and predict structural responses under extreme seismic conditions [4–6].

The application of liquefaction modeling goes far beyond hazard prediction and extends to various fields of geotechnical and structural engineering. Analytical, numerical, and data-driven models enable engineers to estimate post-liquefaction settlements, lateral displacements, and stiffness degradation of soil layers, which are crucial for soil improvement and foundation design. Modeling also allows evaluation of the influence of key parameters such as soil density, fines content, groundwater level, and seismic intensity on the potential of liquefaction. This approach is particularly important in coastal areas, ports, and urban zones where critical infrastructure is founded on soft, saturated sediments. Furthermore, data-driven liquefaction models can aid in the development of liquefaction hazard maps and early warning systems, thereby helping to minimize both economic and human losses in future earthquakes.

Despite these advancements, modeling liquefaction remains a challenging task. Traditional empirical correlations are valid only for specific site conditions and fail to capture the complex, nonlinear interactions between soil parameters [4–6]. Numerical models, while physically detailed, require accurate soil constitutive parameters that can only be obtained through costly and time-consuming laboratory tests. In addition, many regions lack sufficient field data such as SPT or CPT results, limiting the reliability of these models. Furthermore, liquefaction is inherently stochastic, making it difficult to predict with deterministic analytical methods. These limitations highlight the need for intelligent, data-driven approaches that can effectively handle the uncertainty and complexity inherent in liquefaction modeling.

In recent years, artificial neural networks (ANNs) have emerged as powerful tools for modeling the nonlinear and multivariate relationships associated with soil liquefaction [7–9]. Inspired by the human brain, ANNs can learn complex dependencies between input variables such as peak ground acceleration (PGA), groundwater depth, SPT blow count, CPT tip resistance, and shear-wave velocity (Vs30) without requiring explicit mathematical formulations. Once trained on real-world field data, neural networks can accurately predict the probability of liquefaction occurrence as well as its impact on structural stability. Their advantages include adaptability to new datasets, high predictive accuracy, and minimal dependency on physical model assumptions. Moreover, hybrid methods combining ANNs with metaheuristic optimization algorithms—such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO)—have significantly improved model precision and convergence. Overall, the application of artificial neural networks represents a modern and efficient approach for predicting soil behavior under liquefaction conditions and assessing the seismic resilience of structures.

The structure of the paper is as follows: Section 2 reviews existing methods for modeling soil liquefaction. Section 3 introduces the proposed method based on an ANN optimized using the Non-dominated Sorting Genetic Algorithm III (NSGA-III). Section 4 presents the simulation results and evaluates the model's performance, and Section 5 summarizes the main conclusions of the study.

2. Existing Methods

Liquefaction is recognized as one of the most severe defects of granular soils. This phenomenon is mostly observed when loose soil is subjected to dynamic loading or an earthquake. In the study [1], the liquefaction of loose soil is evaluated, and several recommendations are provided. A two-dimensional numerical analysis was conducted to simulate the behavior of the loose soil under dynamic loads. The studied model was implemented on multi-layered soil that was reinforced with stone columns and subjected to dynamic loading. It was observed that soil behavior was improved by the stone columns and that the resulting damage was reduced. Liquefaction of the loose soil can be limited by increasing the soil's shear parameters. Since the damages caused by dynamic loading are time-dependent, the corresponding damage is increased as the duration of the applied load is extended. Moreover, many straining effects were evaluated, and a comparative study was presented, including excess pore water pressure, total vertical displacement, soil deformation, and velocity.

Liquefaction, in which soil strength and stiffness are reduced by seismic or dynamic effects, has caused major earthquake damages worldwide. Soil behavior is modeled to predict liquefaction, and among existing models, UBC3D-PLM is used for this purpose. In the study [2], its capabilities are evaluated by simulating seismic impacts on buildings of different heights using PLAXIS. Data from the 1990 Upland earthquake near Los Angeles was applied. The results revealed significant discrepancies between actual soil behavior and elastic assumptions, underscoring the necessity of employing UBC3D-PLM in seismic assessments.

Recent methods for measuring and preventing soil liquefaction are reviewed in [3]. Tests such as Standard Penetration, Cone Penetration, shear wave velocity, cyclic simple shear, and triaxial are used to evaluate liquefaction potential. Ground improvement techniques, including soil compaction, vibro compaction, deep soil mixing, and reinforcement are applied to reduce risk. Advanced numerical modeling and artificial intelligence techniques have been widely employed for liquefaction prediction. Additionally, seismic design codes, zoning regulations, and community education initiatives are implemented and promoted to

mitigate the adverse effects of liquefaction. These approaches provide a foundation for resilient infrastructure in seismic-prone areas.

The impact of soil liquefaction on pile-supported buildings is investigated in the study [4]. Structural responses and potential consequences when the ground temporarily loses strength during seismic events are analyzed. Measures such as thorough ground investigations, ground improvement techniques, and careful engineering and design are recommended to reduce risks. This research provides insights for enhancing structural stability and supporting the design of earthquake-resistant buildings in liquefaction-prone areas.

The performance of anchor piles in offshore facilities, particularly floating wind turbines, is evaluated using advanced liquefaction modeling [5]. Nonlinear analyses are conducted in FLAC3D using the SANISAND model, which has demonstrated strong capability in accurately simulating pore pressure generation. The results indicate that lateral displacements and tilting of anchor piles may occur due to the combined effects of earthquake shaking and static loads, ultimately leading to soil liquefaction.

Results indicate that lateral displacements and tilting of anchor piles can occur due to combined earthquake shaking and static loads leading to soil liquefaction.

In the study [6], the liquefaction response of railway embankments on fine-grained soils was predicted using an enhanced machine learning (EML) approach based on ANN, ANFIS, and metaheuristic optimization. Machine learning techniques are employed to perform nonlinear multivariate approximations. Ten EML models were evaluated, and results showed high accuracy in predicting the factor of safety (FS) against liquefaction. The ANFIS-FF model, with R^2 values of 91% and 85% for training and testing, was found to be the most successful. The findings demonstrate that the ANFIS-based EML model is more reliable than existing methods for predicting liquefaction development and evaluating the dynamic soil behavior of railway embankments constructed on fine-grained soils.

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

To improve prediction accuracy, a stacked ensemble-learning model with Bayesian optimization (BO-stacking) is introduced [8]. Primary algorithms, including decision trees, support vector machines, and k-nearest neighbors, along with random forest as a secondary algorithm, are employed, and Bayesian optimization is applied to adjust hyperparameters. Input selection is performed using the information gain technique. Results show that BO-stacking outperforms single prediction models, achieving testing accuracy and AUC of 0.913 and 0.992, respectively.

This study demonstrates that BO-stacking is a reliable alternative for predicting soil liquefaction and that the combination of BO and stacking is effective in model training. Several other methods are also available.

The K-Nearest Neighbors (KNN) method is employed for nonlinear regression and is well known for its robustness against outliers while maintaining strong predictive accuracy [9]. The Decision Tree (DT) algorithm offers high computational speed and can generate practical, data-driven results within a short time frame [10]. In scenarios with limited training data, SVM demonstrates superior performance owing to its strong generalization ability and effective information retention [11].

3. Proposed Method

In this study, a feedforward ANN is employed to model the impact of soil liquefaction on structural stability (Figure 1). This type of network is highly effective due to its strong capability in approximating nonlinear functions and learning complex relationships between input and output variables, making it one of the most powerful tools in geotechnical analysis [12-20]. The general structure 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 equipped with ReLU activation functions to enhance nonlinear discrimination capability, and an output layer based on the softmax function that determines the probability of liquefaction occurrence or non-occurrence. Consequently, the network can perform binary classification on multidimensional data and provide more accurate predictions compared to conventional statistical approaches.

3.1. Structural Hyperparameters

In designing a neural network, several parameters significantly affect 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 type of activation functions, and the connectivity 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 an optimal combination of these parameters can be obtained through an optimization algorithm. Proper selection of the number of neurons directly impacts the network's learning capacity, convergence speed, and prevention of overfitting. Additionally, the choice of activation function (ReLU, tanh, or sigmoid) can influence the network's nonlinear behavior and the way it processes signals.

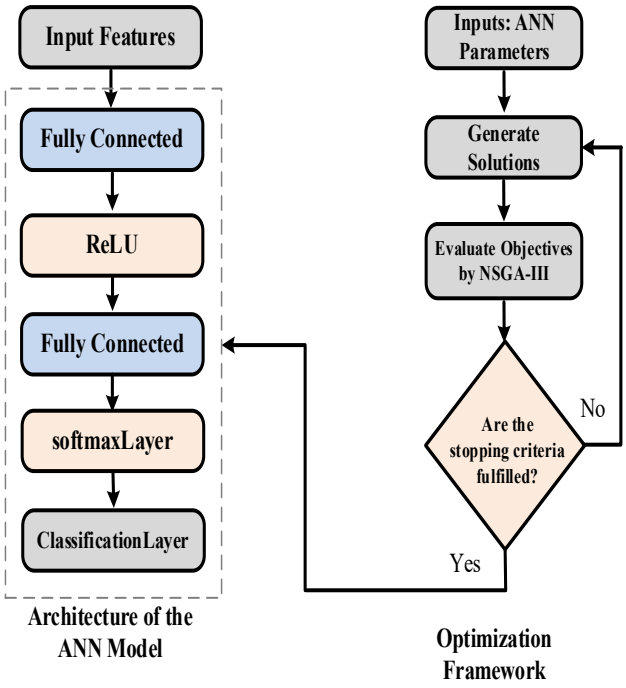

Figure 1. Flowchart of the Proposed Method.

3.2. Multi-objectives

In this study, two primary objectives have been defined for optimizing the neural network to enhance the model's performance in terms of both accuracy and efficiency. The first objective aims to maximize the model's classification accuracy. This ensures that the neural network effectively captures the complex relationships between input features and output classes, accurately classifying samples as either liquefaction or non-liquefaction. Metrics such as Accuracy, F1-Score, Precision, and Recall are used to quantitatively evaluate the model's predictive performance and provide a reliable basis for comparison.

The second objective aims at minimizing the model's complexity, which in this study is measured by the network training time. This objective is particularly important in engineering applications because reducing training time not only conserves computational resources but also enables faster deployment of the model in real-world scenarios. Moreover, shorter training times are often associated with simpler models, which help reduce overfitting and improve the generalization capability of the network.

Given these two objectives, the problem is formulated as a multi-objective optimization task. The goal of this approach is to find an optimal balance between high accuracy and fast training, as excessively increasing accuracy can lead to higher complexity and longer training time, and vice versa. Multi-objective algorithms such as NSGA-III allow generating a set of optimal models with different trade-offs, from which the researcher can select the model that best fits the project requirements [21-25].

3.3. Proposed Procedure

In this study, the overall procedure of the proposed method comprises several systematic steps, ranging from data preparation to the selection of the final model. Initially, raw data, including geotechnical features, seismic parameters, and groundwater levels, are collected. Since these data often have different scales, they are normalized prior to training using methods such as Min-Max normalization or Z-score standardization to minimize the impact of heterogeneous scales on the learning process. The dataset is then divided into training, validation, and testing sets to allow independent evaluation of the model's performance.

In the second step, the search space for the structural hyperparameters of the network is defined. This space includes ranges for the number of neurons in each hidden layer, the number of network layers, and the type of activation function. The purpose of defining these ranges is to provide a reasonable domain for the NSGA-III algorithm to explore possible network structures. For example, the number of neurons in the first layer is considered between 10 and 100, and in the second layer between 5 and 50.

In the third step, the NSGA-III is employed to optimize the hyperparameters. At this stage, each combination of network parameters is treated as an individual in the algorithm's population. For each individual, a neural network with the corresponding specifications is constructed and trained. Then, the model accuracy and training time are calculated and returned as objective functions to the algorithm.

After evaluating all individual's, non-dominated sorting is first performed to identify the Pareto fronts. Unlike NSGA-II, which uses crowding distance to maintain diversity, NSGA-III employs reference points (or reference directions) to allocate and preserve diversity in the objective space. Briefly, the process is as follows: (1) the population is ranked according to the Pareto fronts; (2) full fronts are accepted sequentially until the population size is filled; (3) when selection among individuals in a boundary front is required, each individual is assigned to the nearest reference point; (4) for each reference point, the number of assigned individuals is counted, and the corresponding individuals are selected to ensure a uniform coverage of the reference points. In this way, NSGA-III maintains diversity along the objective axes using reference-based allocation. This reference-driven mechanism significantly enhances NSGA-III's capability in handling multi-objective problems with more than two objectives and complex objective spaces.

In the fifth step, genetic operators, including crossover and mutation, are applied to generate new generations of network structures, maintaining population diversity and preventing premature convergence to local optima. This process continues until the convergence criteria are satisfied or a predetermined number of generations is reached.

Finally, from the set of models on the Pareto front, a model is selected that provides the best balance between high accuracy and low complexity. This final model represents the optimized neural network structure and is then evaluated on the testing data to assess its real performance in predicting soil liquefaction and its impact on structural stability.

Pseudo-code is summarized as follows:

1. Data Preparation:

   Normalize the data (Min-Max or Z-score). Split into training + validation and testing sets. Apply class balancing if needed.

2. Define Parameter Space:

   Specify ranges for network hyperparameters and any constraints.

3. Initialize Population:

   Create an initial population P of size N.

4. Optimization Loop:

```
for gen = 1 to maxGen
    parallel for each individual i in P do
        build network according to genome(i)
        tic; train net; t = toc
        evaluate performanceMetric (AUC)
        f1 = 1 - performanceMetric
        f2 = t
    end
    NSGA-III: non-dominated sorting +
selection + crossover + mutation -> new P
end
```

5. Final Evaluation:

   Report metrics and choose the final model(s).

4. Simulation Results

The algorithms for both the proposed and baseline methods were implemented in MATLAB R2025a (MathWorks) and executed on a high-performance workstation equipped with an Intel® Core™ i9-13900K (24 cores, 5.8 GHz max turbo), 64 GB DDR5 RAM, and a 1 TB NVMe SSD.

The Next Generation Liquefaction (NGL) database is a comprehensive and internationally recognized resource developed to improve the understanding and prediction of soil liquefaction phenomena. It contains a large collection of well-documented case histories of liquefaction and non-liquefaction occurrences from various seismic events around the world. The data include detailed information on soil layer properties, results from in-situ tests such as SPT, CPT, and shear wave velocity (Vs) measurements, as well as groundwater conditions and local ground motion parameters. The primary goal of the NGL project is to provide a standardized and reliable platform for collecting, sharing, and maintaining high-quality field data to support the development and validation of liquefaction prediction models. The database has been established and maintained through collaboration among several leading research and industry organizations, including PEER, USGS, and GEER.

Through its web-based interface, users can search, filter, and download datasets, as well as access detailed case descriptions that include site conditions, earthquake information, geotechnical characteristics, and analysis results. Furthermore, NGL provides analytical and visualization tools that enable comparison between field observations and model predictions [28].

To ensure a fair and consistent evaluation, the available dataset was systematically divided into three independent subsets. The majority portion (70%) was assigned for model training to capture the underlying data patterns, while a separate 15% was employed for validation, allowing adjustment of hyperparameters and monitoring of learning stability. The final 15% of the data was exclusively reserved for testing, ensuring that the performance of the trained model was assessed on completely unseen samples. This data partitioning strategy helps maintain objectivity in the evaluation phase and reduces the risk of information leakage between training and testing stages, thereby enhancing the credibility of the experimental results.

Table 1 presents the selected parameters for the NSGA-III algorithm employed in this work.

Table 1. Parameters of the NSGA-III Algorithm.

Parameter	Value
Maximum number of generations	250
Population size (nPop)	100
Crossover probability (pCrossover)	0.5
Number of parents	2×round(pCrossover×nPop/2)
Mutation probability (pMutation)	0.05
Number of mutated individuals	round(pMutation×nPop)
Mutation rate	0.2
Mutation step size	0.1×(VarMax−VarMin)

VarMin and VarMax represent the lower and upper bounds of the decision variables, respectively. During the training process of the proposed neural network, the performance of the model was continuously monitored across successive epochs to ensure stable and effective learning behavior. As the number of training iterations increased, the classification accuracy showed a smooth and consistent upward trend, demonstrating the model's growing capability to correctly distinguish between different classes. At the same time, the loss function exhibited a steady decline, which reflects the network's progressive reduction of prediction errors and its ability to capture the underlying structure and discriminative features present in the dataset. This overall behavior indicates that the network is converging properly, following a stable learning trajectory without sudden fluctuations or divergence. Such consistent changes in accuracy and loss further suggest that the model is benefiting from a well-balanced configuration of hyperparameters and training settings. Figure 2 illustrates these training dynamics, where the continual increase in accuracy and the monotonic decrease in loss are clearly observable.

The observed trends validate the suitability of the selected network architecture and confirm that the hyperparameters optimized using the NSGA-III algorithm

effectively guide the learning process. By ensuring a controlled balance between model complexity and learning efficiency, the optimized settings help prevent premature overfitting and allow the network to extract meaningful patterns from the input data. Consequently, the model achieves reliable convergence and maintains strong generalization capability, reinforcing the effectiveness of the proposed training strategy.

Table 2 summarizes the optimized hyperparameters of the proposed feedforward neural network. The first hidden layer contains 32 neurons, while the second hidden layer has 16 neurons, providing a balance between learning capacity and prevention of overfitting. ReLU is employed as the activation function to ensure efficient nonlinear mapping and fast convergence. The network is trained using a batch size of 32 samples with a learning rate of 0.001 and He weight initialization. A total of 600 epochs are used, which allows the network to converge effectively without excessive overfitting. These parameters represent the final optimized configuration obtained through careful tuning and are used for all subsequent simulations.

Table 2. Optimized Hyperparameters of the Proposed Neural Network.

Parameter	Value
Number of neurons (Hidden Layer 1)	32
Number of neurons (Hidden Layer 2)	16
Activation function	ReLU
Learning rate	0.001
Batch size	32
Number of epochs	600

The Pareto Optimal Front (POF) represents the set of non-dominated solutions obtained from the multi-objective optimization using NSGA-III. Each point on the front corresponds to a neural network configuration that achieves the best possible trade-off between maximizing accuracy and minimizing training time for soil liquefaction prediction. Figure 3 illustrates the Pareto front obtained after completing all generations of the optimization algorithm. As shown in the figure, the distribution of solutions along the Pareto front illustrates a clear trade-off between classification accuracy and training time. While several configurations achieve high accuracy with reasonably low training time, the figure also shows that pushing either objective to its extreme typically comes at the expense of the other. For instance, the leftmost region of the front includes configurations with minimal training time; however, these solutions tend to exhibit slightly reduced accuracy because they rely on simpler model settings or less extensive training. Conversely, the rightmost region contains configurations that deliver the highest accuracy, but they do so at the cost of significantly longer training times, reflecting the need for deeper architectures or more computationally expensive hyperparameter choices.

The curvature and spread of the front further highlight practical considerations: points located near the central region represent balanced configurations that provide substantial gains in accuracy without a dramatic increase in training cost. Such solutions are often preferred in real-world deployment, where both predictive performance and computational efficiency are critical. Moreover, the density of solutions in different parts of the curve indicates where meaningful improvements are achievable and where diminishing returns begin to appear.

Overall, the figure emphasizes the inherent nature of multi-objective optimization in this problem. Rather than identifying a single best solution, the Pareto front provides a spectrum of optimal trade-offs, enabling practitioners to select the most suitable configuration depending on application-specific constraints—such as real-time requirements, hardware limitations, or the necessity for maximum accuracy. This deeper interpretation clarifies the practical implications of the front and underscores its value in guiding informed and context-aware model selection.

By examining the Pareto front, researchers and engineers can select a neural network configuration that best fits the computational constraints and desired predictive performance. The front also provides insight into the sensitivity of the model to different hyperparameter combinations, ensuring robust decision-making in designing ANNs for soil liquefaction modeling.

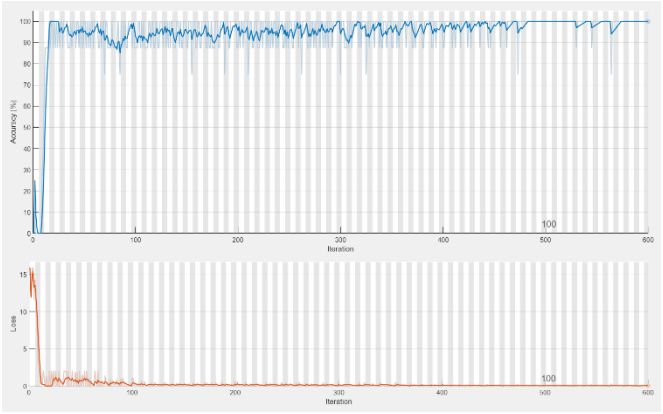

Figure 2. Training performance of the proposed ANN. The plot shows the increase in accuracy and decrease in loss over successive epochs.

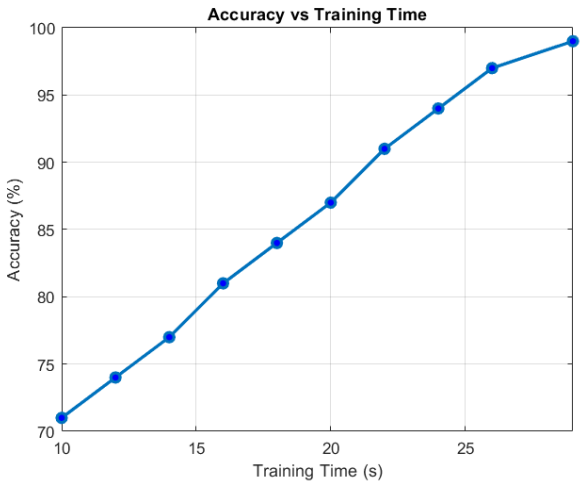

Figure 3. Pareto Optimal Front of the proposed ANN showing the trade-off between training time and classification accuracy.

To further evaluate the robustness of the proposed framework, a complementary experiment was conducted in which the hyperparameters of the artificial neural network were intentionally selected without optimization as shown in the Figure 4. In this setup, the number of neurons in the hidden layers, learning rate, and batch size were fixed at arbitrary values that did not result from the NSGA-III search process. Specifically, the first and second hidden layers were assigned 20 and 10 neurons, respectively, and the learning rate was set to 0.01 without adaptive adjustment. The results demonstrated a noticeable degradation in classification accuracy and training stability compared to the optimized configuration. The final test accuracy dropped from approximately 99.8% (in the optimized scenario) to nearly 85%, confirming that the selected hyperparameters failed to capture the nonlinear relationships among the input features effectively. Furthermore, the non-optimized model required a longer training time per epoch without significant improvement in performance, which reflects an inefficient use of computational resources.

This analysis highlights the crucial role of hyperparameter tuning in neural network modeling. By contrasting the optimized and non-optimized configurations, it becomes evident that the use of NSGA-III not only enhances the predictive accuracy but also ensures an efficient balance between model complexity and training effort.

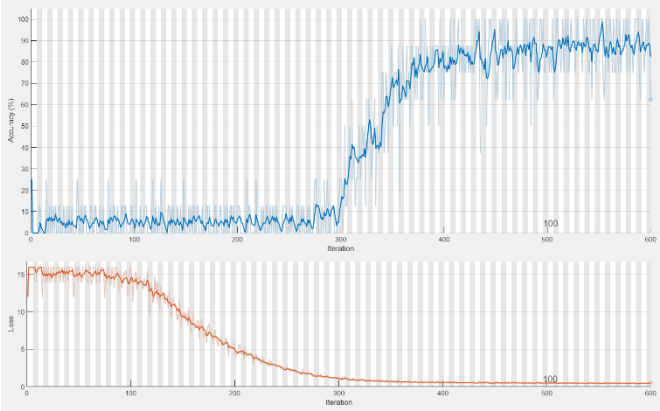

Figure 4. Pareto Optimal Front of the proposed ANN showing the trade-off between training time and classification accuracy.

In this study, the Accuracy, F1-Score, Precision, and Recall curves are presented in Figures 5 to 8 to illustrate how the model's performance evolves during training and evaluation. These curves clearly show that the proposed method achieves stable learning behavior, consistent convergence, and strong predictive quality. The smooth and upward trend of the performance metrics indicates that the selected network configuration and the optimization strategy effectively enhance the model's performance while avoiding instability or oscillations during the learning process.

To assess the final performance, the proposed method was compared with several widely used approaches, including KNN [9], Decision Tree [10], SVM [11], and Stacking [8]. Based on the obtained results, the proposed model achieved the highest performance with an accuracy of approximately 99.8%, whereas the best competing method (Stacking) reached 99.2%. Methods such as KNN and SVM demonstrated weaker performance, and although the Decision Tree achieved acceptable accuracy, it still underperformed compared to the proposed approach. These comparisons show that the proposed method surpasses existing techniques not only in terms of accuracy but also across F1-Score, Precision, and Recall, providing a well-balanced trade-off between correctly identifying positive samples and minimizing misclassifications.

The primary reason for this superiority lies in the use of a multi-objective optimization strategy based on the NSGA-III algorithm for selecting the network architecture and tuning the hyperparameters. Unlike traditional methods that rely on fixed settings or simple search techniques, the proposed model systematically explores a wide range of possible configurations and selects the structure that best balances high accuracy with reasonable training time. Through Pareto-based selection and reference-point guidance, NSGA-III prioritizes architectures that achieve strong predictive performance without unnecessary complexity, resulting in a network that is efficient, stable, and resistant to overfitting.

Another key factor contributing to the performance improvement is the coherent selection of activation functions, the number of neurons, and the network depth—all jointly optimized by the evolutionary algorithm. This enables the model to capture nonlinear patterns in the data more effectively. In contrast, conventional methods such as KNN or SVM lack the flexibility to model such complex relationships, and even ensemble-based methods like Stacking do not incorporate an automated mechanism for simultaneous multi-parameter optimization.

Overall, the combination of a neural network with multi-objective evolutionary optimization enables the proposed method to achieve superior accuracy, generalization capability, stability, and computational efficiency. These results confirm that for complex real-world problems, employing an intelligent optimization framework can significantly enhance model performance beyond what traditional machine learning methods can deliver.

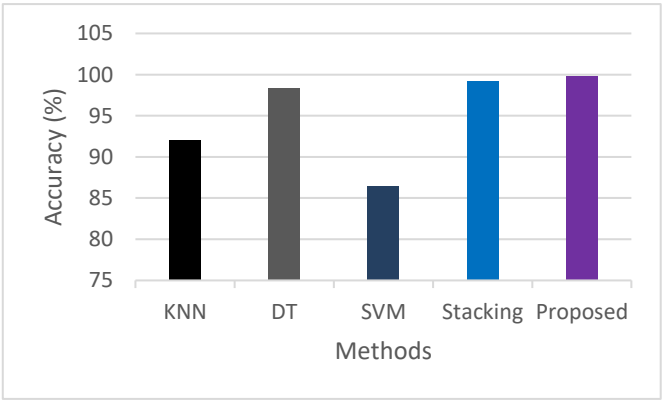

Figure 5. Comparative analysis of model accuracy for the proposed approach and existing methods.

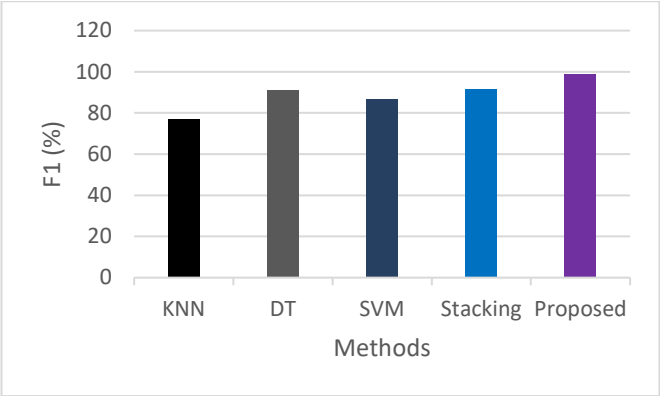

Figure 6. Comparative analysis of model F1-Score for the proposed approach and existing methods.

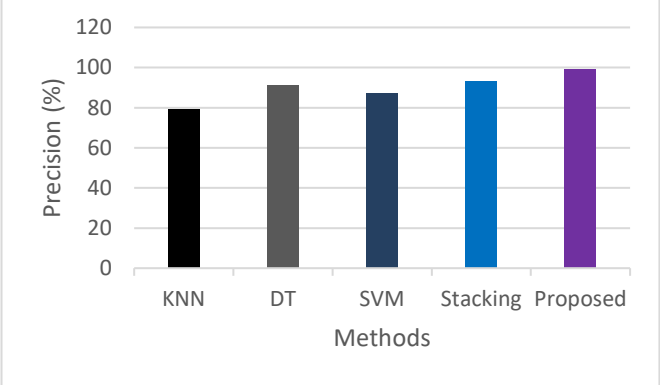

Figure 7. Comparative analysis of model Precision for the proposed approach and existing methods.

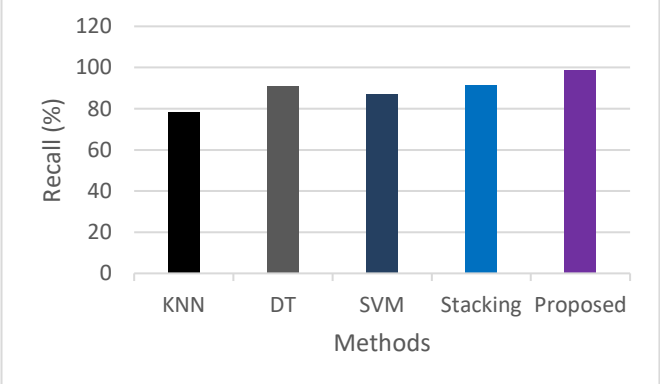

Figure 8. Comparative analysis of model Recall for the proposed approach and existing methods.

5. Limitations and Future Work

Despite the promising performance of the proposed NSGA-III–ANN framework in predicting the impact of soil liquefaction on structural stability, several limitations should be acknowledged, which also provide directions for future research:

1- Real-world deployment considerations: Implementing the framework under field conditions may face challenges related to computational requirements, sensor accuracy, and data acquisition constraints.

2- Data variability: The model's performance can be affected by heterogeneous soil conditions, variability in seismic inputs, and uncertainties in geotechnical measurements, which may reduce prediction reliability under unobserved scenarios.

3- Integration with physical models: Hybrid approaches that combine the ANN model with physics-based or numerical models could enhance interpretability and robustness of predictions, enabling more reliable assessments of liquefaction effects.

Addressing these limitations in future studies can improve the practical applicability of the framework and provide more comprehensive insights for seismic design, risk assessment, and mitigation strategies in geotechnical engineering.

6. Conclusions

This paper investigated innovative approaches to improve the efficiency of CIGS chalcopyrite thin film solar cells and using advanced techniques and optimization in layer design, including the use of ITO anti-reflection layer,

In this study, a multi-objective optimization framework based on NSGA-III was combined with a feedforward artificial neural network to model the impact of soil liquefaction on structural stability. The proposed approach aimed to simultaneously maximize classification accuracy while minimizing model complexity and training time. The optimization algorithm systematically explored various network architectures and hyperparameter combinations, ultimately selecting the configurations that achieved the best trade-off between performance and computational efficiency. The experimental results demonstrated that the proposed method outperformed conventional techniques, including KNN, Decision Tree, SVM, and Stacking, in terms of Accuracy, F1-Score, Precision, and Recall. The final model achieved an accuracy of 99.8%, with F1-Score, Precision, and Recall all exceeding 98%. This clearly highlights the effectiveness of the multi-objective optimization strategy in improving the predictive capability of neural networks for complex geotechnical problems. One of the main strengths of the proposed framework lies in its ability to automatically adjust structural hyperparameters, such as the number of neurons in hidden layers and activation functions, based on the Pareto front generated by NSGA-III. This capability ensures that the network not only achieves high predictive performance but also avoids overfitting and reduces unnecessary computational overhead. Additionally, the study confirmed that incorporating multi-objective optimization into ANN design is particularly valuable for geotechnical applications, where data often exhibit nonlinear relationships and variability across different sites. The framework provides a systematic and reproducible methodology for selecting the most effective network configuration, which can be adapted to other prediction tasks in civil and structural engineering.

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