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Prediction of Soil Liquefaction Using a Multi-Algorithm Technique: Stacking Ensemble Techniques and Bayesian Optimization

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ABSTRACT

Historically, liquefaction has caused a number of earthquake-related risks. When granular soils get saturated, liquefaction may occur during an earthquake, which can have devastating effects. Therefore, it is essential, especially in the context of civil and structural project planning, to have the capacity to precisely predict soil liquefaction potential. Therefore, the stacked ensemble-learning model with Bayesian optimization (BO-stacking) is introduced to make predictions of soil liquefaction more accurate. It was constructed utilizing primary algorithms like decision trees, support vector machines, and k-nearest neighbors, as well as secondary algorithms like the random forest algorithm. A Bayesian optimization method is also used to improve the accuracy of the predictions of soil liquefaction by adjusting the hyperparameters of these four classification algorithms. Information gain technique also was used for input selection. The results show that BO-stacking outperformed single prediction models. The testing accuracy and ACU of this model was 0.913 and 0.992, respectively. This study indicates that BO-stacking is a feasible alternative to established techniques for predicting soil liquefaction. In addition, the results of this study indicate that the BO and stacking approaches are effective in training the prediction model when used in conjunction.

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1. Introduction

The term "liquefaction" describes the change in state from solid to liquid that may happen in granular soils as pore water pressure increases [1,2]. Excessive granular soil liquefaction as a result of seismic loadings is a major problem for geotechnical engineers. The unpredictability of the resulting lateral spreading of soil mass poses a significant hazard to the region's civil engineering structures, which is why preventing such events is so important [1–3]. When the Ms 8.0 Wenchuan earthquake struck China in 2008, for example, it caused widespread liquefaction and the subsequent destruction of surface buildings and subsurface infrastructure [1,2,4]. As a result, civil engineering projects cannot be planned without first assessing the soil's liquefaction potential [5–8].

Liquefaction, in the context of environmental science, refers to a phenomenon where saturated soil or other unconsolidated materials lose their strength and behave like a liquid under certain conditions [9]. It is commonly associated with seismic events such as earthquakes, but it can also occur due to other factors like intense vibration or changes in groundwater levels [9]. Liquefaction can lead to significant geological hazards. When liquefaction occurs during an earthquake, it can cause the ground to lose its stability, resulting in landslides, slope failures, and the collapse of structures [10]. In addition, liquefaction is an important consideration in seismic risk assessments. By studying the geological and geotechnical properties of an area, including soil liquefaction potential, scientists and engineers can estimate the potential damage caused by an earthquake. Moreover, liquefaction can have environmental impacts beyond immediate geological hazards [11]. For example, in coastal regions, liquefaction can cause the release of trapped gases, such as methane, which can contribute to greenhouse gas emissions and climate change.

Various techniques for measuring the potential liquefaction of soil have been suggested in the literature (e.g., [12–14]). A significant proportion of the techniques, such as the cone penetration tests (CPTs), the shear wave velocity technique (SWV), the standard penetration tests (SPTs), the self-boring pressure meters (SBPTs), and the flat dilatometer tests (DMTs), are often dependent upon the splitting of non-liquefaction sectors from the liquefaction sections. This is ascertained by taking into consideration the in-situ findings in locations where experiment information can be found [2,15–17]. As both the soil and the earthquakes are very hard to predict, it is hard to come up with a single empirical formula to use in linear regression. Consequently, many researchers have focused on developing analytical models that are easier to implement and more accurate in analyzing soil liquefaction compared to traditional empirical equations.

In estimating liquefaction potential, artificial neural network (ANN)-based models have been used most often [18–21]. Although ANNs have been shown to be more effective than statistical approaches [22,23], they have significant drawbacks such as slow convergence speed, overfitting, and a tendency to converge to local minima, a lack of generalizability, and so on [24,25]. To address these limitations, researchers have explored alternative machine learning (ML) techniques and hybrid approaches for soil liquefaction prediction.

Muduli and Das [26] devised the multi-gene genetic programming (MGGP) strategy to assess the soil's liquefaction potential using post-liquefaction CPT and SPT data. As a novel method of liquefaction measurement, it merits widespread dissemination and support. A group method of data handling model was built using neuro-fuzzy techniques by Javdanian, et al. [27] which was enhanced by the application of particle swarm optimization. This approach has been demonstrated to be valid and trustworthy in this setting. Additionally, Hoang and Bui [28] used a combination of least squares support vector machines and kernel Fisher discriminant analysis to make predictions about soil liquefaction. Their findings demonstrated the feasibility and dependability of the suggested model in this context.

Recent studies have explored ensemble learning techniques and hybrid models to leverage the strengths of multiple algorithms and improve prediction accuracy [29–33]. Kurnaz and Kaya [34] proposed the ensemble group approach to data handling to forecast soil liquefaction. Their findings contrasted well with those of the traditional group approach to data handling, suggesting that their model is superior at forecasting soil liquefaction. The fuzzy support vector machine described by Rahbarzare and Azadi [35] was recently improved using particle swarm optimization and a genetic approach. They demonstrated that particle swarm optimization and genetic algorithms are useful tools for improving fuzzy support vector machine quality. Some researchers [36,37], used Bayesian models to simulate the liquefaction potential. In addition, machine learning (ML) techniques have been used in many other domains for forecasting and optimization purposes and the outcomes suggest they are helpful tools with good [38–54].

Soil liquefaction predictions have often been made using support vector machines (SVM) [55], k-nearest neighbors (KNN) [56], and decision tree (DT) [57] models. In the domain of soil liquefaction prediction, single ML models are not sufficient due to several reasons [58]. Firstly, soil liquefaction is a complex phenomenon influenced by various factors such as soil properties, seismic loadings, and site-specific conditions. It is challenging to capture the intricate relationships and nonlinearities between these factors using a single model. Different ML models have their own strengths and weaknesses, and no single model can effectively capture all the complexities of soil liquefaction. In addition, the hybrid-ML techniques can decrease the computational costs and improve the accuracy as compared to the use of single ML techniques [59]. Therefore, using a combination of multiple models can help to incorporate diverse perspectives and improve prediction accuracy. It is important to mention that hybrid ML models have been successfully used and proposed in engineering [60–66].

Secondly, ML models often require optimization of hyperparameters to achieve the best performance. Optimization methods such as genetic algorithms, differential evolution, and grid search have been used to tune the hyperparameters of individual models Genetic algorithms (GA), differential evolution (DE), grey wolves' optimization (GWO), kernel Fisher discriminant analysis (KFDA), and grid search are only some of the optimization methods that have been used with these approaches [28,56,67–70]. However, the optimization of hyperparameters alone may not yield the highest level of accuracy, as the search space can be vast and complex [71,72]. Combining multiple models and employing well-known optimization techniques, such as

Bayesian optimization algorithm, can enhance the prediction accuracy by effectively exploring the hyperparameter space and finding the optimal configuration for the ensemble of models.

Furthermore, soil liquefaction is a critical geotechnical problem with significant implications for civil and geotechnical engineering. The consequences of inaccurate predictions can be severe, leading to the failure of buildings and infrastructure. By relying solely on a single model, there is a higher risk of making overly optimistic assumptions or not considering all the contributing factors adequately [73]. Using a stacked ensemble learning algorithm, which combines the predictions of multiple models, can help mitigate these risks by leveraging the strengths of each individual model and reducing errors caused by model bias or limitations.

The contributions of this study to the literature and practice are significant. Firstly, this research addresses the issue of soil liquefaction, which is a major concern for geotechnical engineers due to its potential impact on civil engineering structures. By proposing the use of the stacked ensemble learning algorithm with Bayesian optimization (BO-Stacking), this study introduces a novel approach to predict soil liquefaction potential. The combination of single ML models and well-known optimization techniques, such as the Bayesian optimization algorithm [38,43,74], is a unique contribution of this work. It aims to improve the accuracy of predictions by considering multiple models and optimizing their hyperparameters. This research also highlights the limitations of traditional models and techniques commonly used in soil liquefaction prediction, such as SVM, KNN, and DT, and discusses the drawbacks associated with them. By introducing a new methodology that overcomes these limitations, this study provides a valuable alternative for researchers and practitioners in the field. Additionally, the use of ensemble learning and optimization techniques adds to the originality and novelty of this work, as it expands the existing knowledge and offers a more comprehensive approach to soil liquefaction prediction. The detailed discussion of the methodology and the presentation of outcomes and discussions further enhance the relevance and applicability of this research in the field of geotechnical engineering. The remaining sections of the paper are structured as follows: Liquidity in soil is discussed in detail in Section 1.1. The BO-stacking methodology and datasets used in this study are described in more detail in Section 2. Section 3 details the outcomes and the discussion that followed. This research is summarized in Section 4.

2. Methods

2.1. Dataset and its characteristics

China had a catastrophic natural disaster on July 28, 1976, when the Great Tangshan Earthquake happened. The number of fatalities places this earthquake at the top of the list of the twentieth century's most devastating disasters. The earthquake's origin was the industrial city of Tangshan in Hebei, which is home to almost a million people. The initial number of dead estimated was 655,000, but it has now been lowered to between 240 and 255,000, with 164,000 individuals dealing with severe injuries [1].

For the construction of the models discussed in this study, a database from literature [1] is utilized. The focus of this database is the Tangshan Earthquake [75]. The datasets used in this study were collected through post-earthquake field investigations and laboratory tests conducted by researchers and engineers in the affected areas. These investigations involved examining the soil conditions, measuring the groundwater levels, and assessing the severity of liquefaction at various sites. Soil samples were collected from different locations and depths for laboratory analysis, which included determining soil properties such as grain size distribution, plasticity index, and relative density. The collected data was then compiled into a comprehensive database, which has been used in several previous studies on soil liquefaction [1,10,19,76].

To ensure data quality and consistency, the collected datasets were carefully processed and validated. This involved removing samples with insufficient or erroneous information and verifying the accuracy of the measured parameters. The processed dataset was then used as input for the development of the prediction models in this study.

Some samples were excluded from the final analysis due to insufficient or erroneous information. Only the liquefaction possibility was factored into the output of the model. Table 1 lists the variables used in this investigation. The same parameters have been used in the previous studies and they have been selected based on their impacts on liquefaction potential [1,10,19,76]. In each instance, "1" implies that liquefaction has happened, while "0" denotes that it has not. The letter τ_{av} indicates the total cyclic shear stress induced by the earthquake. During the modeling process, 79 unique samples were used. A ratio of 70:30 was used to divide the data into training and test datasets. This work used 5-fold cross-validation to train the BO-stacking model. Test data was then used to evaluate the generated model. The distribution of inputs and target variable before the data split is shown in Figure 1.

Table 1
Variables used in this study.

Variable	Symbol	Unit	Min	Max
Earthquake magnitude	M	-	7.8	7.8
Effective vertical stress	σ'_{v0}	KPa	20.6	120.4
Total vertical stress	σ_v	KPa	16.7	244.2
Mean grain size	D_{50}	mm	0.06	0.48
Water table	d_w	m	0.21	3.6
Peak acceleration at the ground surface	a_{max}	g	0.1	1.1
Depth	d_s	m	0.9	13.1
Measured CPT tip resistance	q_c	MPa	0.98	18.57
Cyclic stress ratio	$\frac{\tau_{av}}{\sigma'_{v0}}$	-	0.08	0.42
Liquefaction*	-	-	0	1

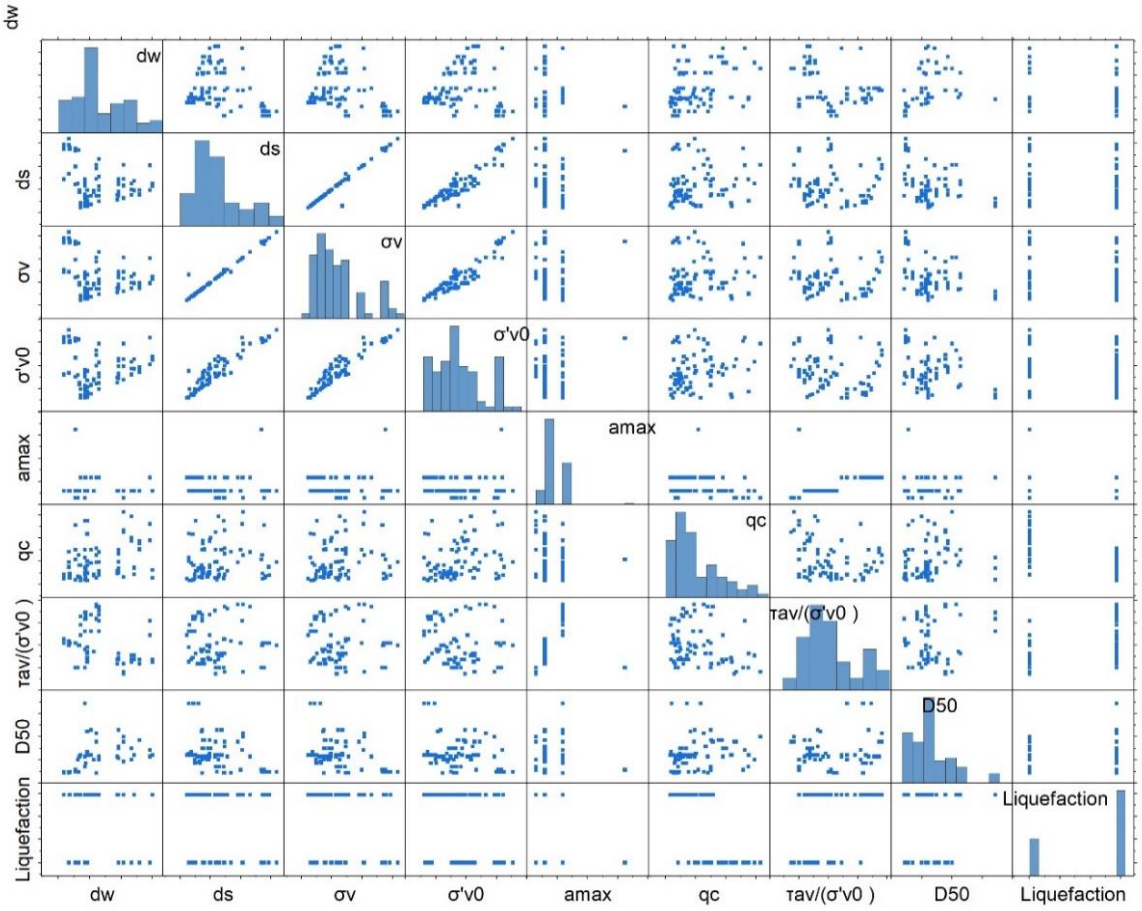


Fig. 1. Relationships between variables in this study.

2.3 Computational resources

The training and evaluation of the BO-stacking model were executed on a high-performance computing system tailored to accommodate the model's complexity, dataset size, and the demand for efficient hyperparameter optimization. This system boasted specifications including an Intel Core i7-11700K CPU running at 3.60 GHz with 8 cores, coupled with 32 GB of DDR4 RAM. Graphics processing was enhanced by an NVIDIA GeForce RTX 3080 GPU featuring 10 GB of GDDR6X memory. Complementing these components, the system was equipped with a 1 TB SSD for storage and a Gigabit Ethernet network interface. Given the computational intensity of Bayesian optimization for tuning hyperparameters, which necessitated training and evaluating multiple models with varied configurations, we harnessed parallel processing and distributed computing methodologies to expedite the optimization process. Employing appropriate libraries or frameworks, we parallelized model training and evaluation across numerous cores or nodes, significantly diminishing computation time.

2.4 Scalability considerations

In anticipation of scalability challenges contingent upon dataset size and complexity, we adopted several preemptive measures. These included feature selection techniques like mutual

information to identify salient features, thereby reducing dimensionality and computational load. Additionally, we conducted data preprocessing steps, such as normalization and categorical variable encoding, to optimize training efficiency. Exploring model compression and pruning techniques further enabled us to diminish the size and complexity of both base learners and the meta-learner without substantial performance compromise. Our computational infrastructure was deliberately designed to scale, accommodating larger datasets or more intricate models by integrating additional resources like nodes or GPUs as needed. These considerations and strategies collectively ensured the BO-stacking model's efficient training and evaluation, even amidst burgeoning dataset complexity and size, while acknowledging that specific computational needs and scalability nuances may vary based on dataset characteristics and performance objectives.

2.2. Learning using ensembles and optimization techniques

2.2.1. Stacking ensemble learning model

Many different types of ML may be combined into one using the stacking ensemble learning approach. A "meta-classifier" or "meta-regression" is a model that combines the results of many classifiers or regressions. In other words, many base learners (first-level learners) are trained, and their outcomes are utilized as the input of the second-level learners in the following step. Ultimately, meta-learners acquire the final forecast findings.

The rationale behind choosing a stacking ensemble learning approach is to leverage the strengths of multiple individual models and combine their predictions to improve overall performance. By using a diverse set of base learners, such as k-nearest neighbors (KNN), support vector machine (SVM), and decision tree (DT) algorithms, the stacking ensemble model can capture different aspects of the relationships between the input features and the target variable. Each base learner has its own unique assumptions, biases, and capabilities, and by combining their outputs, the ensemble model can compensate for the weaknesses of individual models and enhance the robustness and accuracy of the predictions.

Random forest (RF) was selected as the secondary learner in the stacking ensemble model due to its ability to effectively handle the outputs of the base learners and provide a final prediction. RF is an ensemble learning method that constructs multiple decision trees and aggregates their predictions through voting or averaging. It has several advantages, such as its ability to handle high-dimensional data, reduce overfitting, and capture complex non-linear relationships. By using RF as the meta-learner, the stacking ensemble model can learn from the diverse set of base learners and make more accurate and reliable predictions.

As seen in Figure 2, the two-layer stacking ensemble learning approach is primarily employed in this work to investigate soil liquefaction. The base learners are the k-nearest neighbors (KNN), the support vector machine (SVM), and the decision tree (DT) algorithms, and the second-level learner is the random forest (RF) algorithm. Once the stacking ensemble-learning model was made, it was not possible to utilize all of the training datasets for testing. This would prevent the occurrence of overfitting; the impact was positive on the trained data but unfavorable on the test datasets, which were used to generate the final forecast. Over-fitting can be reduced to some

extent by using k-fold cross-validation to check how well the model predicts [43,54,77–79], especially how well the trained model works on data it has never seen before. Consequently, the k-fold cross-validation approach may output the findings of every sample subset to tackle the overfitting issue. In this investigation, a 5-fold was used.

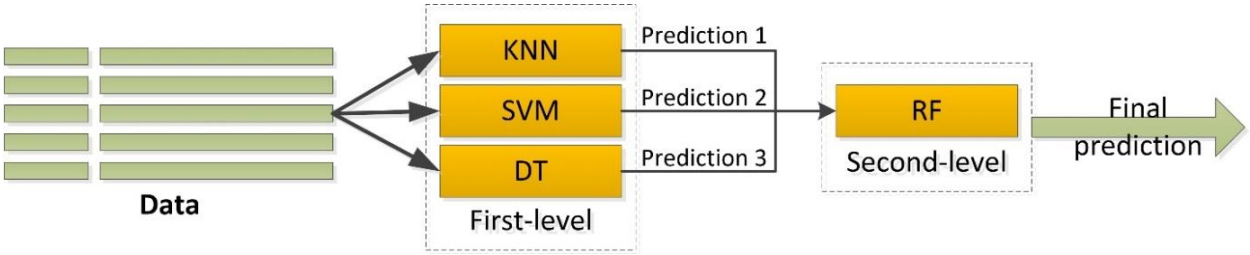


Fig. 2. Process of stacking ensemble learning.

2.2.2. Bayesian optimization

In ML, parameter modification is a tiresome but necessary process. As there are several hyper parameters in each model, these factors together impact the effectiveness of these algorithms. Therefore, manually adjusting parameters could not optimize the algorithm's performance. In this work, however, Bayesian optimization (BO), a mathematical technique, was used to intelligently modify hyper parameters. The least value of the objective function is estimated using the BO technique, which is based on the notion that a replacement function (probability model) is derived from the results of previous objective function evaluations [80,81]. Consequently, it may be used efficiently when the computation is difficult and the number of iterations required is substantial [82]. Unlike grid search [83] and random search [84], the BO utilizes the Bayesian theorem to determine the posterior distribution of the objective function and then selects the hyper parameter configuration for the subsequent sample based on the distribution. The goal of optimization is to learn the form of the objective function and then choose the parameters that maximize the global outcome. In addition to its widespread application in cutting-edge AI, the BO algorithm has been praised for its superiority over other optimization techniques such as the particle swarm optimization algorithm, the genetic algorithm, and others [85,86]. Optimization criteria are determined using the Bayesian theorem and the Gaussian process. To develop a surrogate for the aim and measure its fuzziness, a Bayesian ML strategy is combined with Gaussian process regression. From this substitution, an acquiring function can be derived to obtain the sample location.

2.2.3. BO-stacking

This research proposes the BO-stacking ensemble learning model. It applied the BO method to three single models, namely the DT [87], SVM [88], and KNN [89] algorithms, and then stacked the three optimized models using the RF algorithm [90] to create a new ML model. Figure 3 illustrates the implementation method.

The key innovation in our methodology is the introduction of the BO-Stacking model for predicting soil liquefaction potential. This model combines stacked ensemble learning with Bayesian optimization to enhance prediction accuracy. By integrating primary algorithms such as decision trees, support vector machines, and k-nearest neighbors, along with the secondary

algorithm of random forest, our model incorporates a diverse set of techniques commonly used in ML. This ensures the versatility and applicability of our approach across various scenarios and datasets. The incorporation of Bayesian optimization further refines the model by fine-tuning the hyperparameters of the classification algorithms, optimizing their performance for soil liquefaction prediction. Additionally, we utilize the information gain technique for input selection, enhancing the effectiveness of the model. This methodology innovation represents a significant contribution to the field as it offers a novel and effective approach for accurately predicting soil liquefaction, thereby aiding in the planning and mitigation of earthquake-related risks in civil and structural projects.

2.3. Performance evaluation

This research used a number of well-established performance criteria for classification to evaluate the effectiveness of the models in predicting soil liquefaction. The specific performance metrics chosen were:

- **Classification Accuracy (CA)**: CA measures the proportion of correctly classified instances (both liquefied and non-liquefied) out of the total instances. It provides an overall assessment of the model's predictive accuracy. CA was chosen because it is a straightforward and widely used metric that gives a general understanding of the model's performance.
- **Area Under the Receiver Operating Characteristic Curve (AUC)**: AUC is a metric that evaluates the model's ability to discriminate between liquefied and non-liquefied instances. It plots the true positive rate against the false positive rate at various classification thresholds. AUC was selected because it is a robust metric that is insensitive to class imbalance and provides a comprehensive assessment of the model's discriminatory power.
- **F1 Score**: The F1 score is the harmonic mean of precision and recall. It balances the model's ability to correctly identify liquefied instances (precision) and its ability to find all liquefied instances (recall). The F1 score was chosen because it provides a single measure that combines both precision and recall, making it a good indicator of the model's overall performance, especially when the classes are imbalanced.
- **Precision**: Precision measures the proportion of correctly predicted liquefied instances out of all instances predicted as liquefied. It indicates the model's ability to avoid false positives. Precision was selected because it is important to minimize false alarms in the context of soil liquefaction prediction, as false positives can lead to unnecessary precautions and higher costs.
- **Recall**: Recall, also known as sensitivity, measures the proportion of correctly predicted liquefied instances out of all actual liquefied instances. It indicates the model's ability to identify all liquefied instances. Recall was chosen because it is crucial to identify as many liquefied instances as possible to ensure appropriate mitigation measures are taken to prevent damage and ensure safety.

These performance metrics were selected to provide a comprehensive evaluation of the models' effectiveness in predicting soil liquefaction. The combination of these metrics allows for a

thorough assessment of the models' predictive accuracy, discriminatory power, and ability to balance precision and recall.

Performance criterion values vary between 0 and 1. The model becomes more accurate as the values increase. In addition, a simple ranking mechanism is used to evaluate the performance of the models in a methodical manner. A model is superior if its cumulative ranking is greater.

3. Results and discussions

3.1. Input selection

Fundamental to geotechnical engineering is the forecasting of soil liquefaction under particular circumstances. By accurately forecasting soil liquefaction and taking into consideration all of its contributing factors, the high cost and risk of developing civil engineering projects may be avoided. Several input factors, including $M, d_w, d_s, \sigma_v, \sigma'_{v0}, a_{max}, q_c, \frac{\tau_{av}}{\sigma'_{v0}}, and\ D_{50}$, are recognized to influence the forecasting of soil liquefaction. However, the relevance of every input variable is uncertain and requires additional investigation.

In this part, the mutual information test technique [91] was employed to study the relevance of the input parameters on soil liquefaction in order to examine and evaluate the sensitivity of various contributing factors to soil liquefaction. Whether linear or nonlinear, the link between an input variable and a target variable may be captured using the filtering technique of mutual information (MI). It displays the strength of the dependency between variables. Information gain may be used to compute the magnitude of the MI between variables:

$$Gain\ (A, B) = Ent(A) - \sum_{q-1}^{q} \frac{|A^q|}{|A|} Ent(A^q) \quad (1)$$

where q denotes the total number of values for B, A_q is the set of A when b equals b_q, and *Ent(A)* symbolizes the information entropy. The better the relationship between A and B, the greater the value of *Gain(A, B)*.

To implement the mutual information test technique for input selection, the following steps were undertaken:

- The mutual information between each input parameter and the target variable (soil liquefaction) was calculated using equation (1).
- The input parameters were then ranked based on their mutual information scores, with higher scores indicating a stronger relationship with the target variable.
- A threshold value for the mutual information score was determined based on the elbow method, which identifies the point of diminishing returns in the ranked scores.
- Input parameters with mutual information scores above the threshold were considered relevant and selected for inclusion in the prediction models.

The criteria used to determine the relevance of input parameters were based on their mutual information scores and their relative importance in predicting soil liquefaction. Input parameters

with higher mutual information scores were considered more relevant, as they exhibited a stronger relationship with the target variable. The elbow method provided an objective approach to determine the cutoff point for selecting relevant input parameters, ensuring that only the most informative variables were included in the models.

The significance of the input parameter that forecasts soil liquefaction was then evaluated based on the variable's score in the MI analysis. The MI selected the five most important variables, including, $d_w, \sigma'_{v0}, a_{max}, q_c, and \frac{\tau_{av}}{\sigma'_{v0}}$ for predicting the soil liquefaction. With these inputs, single ML and stacking models will be made to predict soil liquefaction.

3.2. Optimization of models' parameters

The baseline models were the DT, SVM, and KNN algorithms, while the secondary predictive model was the RF. The implementation processes of these four approaches are detailed in several sources [55,92–94]. Data and models' hyper-parameters are perturbed in order to enhance the classification accuracy of the stacking ensemble model. Concerning datasets, the 5-fold cross-validation procedure is implemented for sample alteration. A Bayesian optimization method is employed to dynamically find the ideal solution by learning the samples, so as to maximize the prediction impact of the model, since each algorithm utilized in this research typically comprises one or more significant hyper-parameters.

For each of the individual models, the following hyperparameters were optimized using Bayesian optimization:

1. Decision Tree (DT):
   - Minimum number of instances in leaves: This parameter determines the minimum number of samples required to be at a leaf node. It was optimized to control the depth and complexity of the tree.
   - Maximum number of splits: This parameter sets the maximum number of split points in the decision tree. It was optimized to find the balance between model complexity and generalization performance.
2. Support Vector Machine (SVM):
   - C (Regularization parameter): The C parameter determines the trade-off between achieving a low training error and a low testing error. It was optimized to control the model's complexity and its ability to generalize well to unseen data.
   - Kernel function: The choice of kernel function defines the mapping of input data into a higher-dimensional feature space. The Radial Basis Function (RBF) kernel was selected as the optimal kernel function during the Bayesian optimization process.
3. K-Nearest Neighbors (KNN):
   - Number of neighbors: This parameter specifies the number of nearest neighbors to consider when making predictions. It was optimized to find the optimal value that maximizes the model's performance.
   - Distance metric: The distance metric determines how the similarity between samples is calculated. The Mahalanobis distance was found to be the optimal metric during the optimization process.

- Distance weight: This parameter controls the influence of neighboring points on the prediction. The uniform weight, where all neighbors are given equal importance, was selected as the optimal setting.

Table 2 lists the hyper-parameters and their optimized values for the four models used in this analysis. By employing Bayesian optimization to fine-tune these hyperparameters, the performance of each individual model was maximized, contributing to the overall accuracy of the stacking ensemble model in predicting soil liquefaction.

Table 2
Hyper-parameters optimized to predict soil liquefaction.

Model	Optimal hyper-parameters
SVM	C = 500; Kernel function = RBF
KNN	No. of neighbors = 5; distance metric = Mahalanobis; Distance weight = uniform
DT	Min No. of instances in leaves: 4; Max no. of splits = 5
RF	No. of trees = 511; min number of splits = 5

3.3. Prediction results

56 data sets were used for training and 23 were used for testing in this analysis. In order to forecast soil liquefaction, each of the three individual models was adopted individually. Following training with these four algorithms, the predictions are made using both the default parameters and the Bayesian optimized parameters. During this time, the stacking ensemble learning technique is being employed in order to merge these three regression models, each of which was improved using the Bayesian approach. After the training was done, the RF was also used as a second predictive model to make predictions. Figure 3 shows how the Stacking ensemble learning model, which uses Bayesian optimization, works step by step. Figure 4 presents, for each individual model and stacking model, the real value, the forecast value after Bayesian optimization. This Figure allows for a more nuanced comparison of the models' performance by showing the breakdown of predicted percentages for each category (0 and 1) and comparing them to the Real Liquefaction percentages. For the KNN model, we can see that it predicts 73.91% for category 1, which is higher than the Real Liquefaction percentage of 60.87%, while it predicts only 26.09% for category 0, which is lower than the actual 39.13%. This indicates that the KNN model tends to overestimate category 1 and underestimate category 0. The SVM and DT models show similar patterns, with their predicted percentages deviating from the Real Liquefaction percentages in both categories. The stacking model, however, demonstrates the closest alignment between its predicted percentages and the Real Liquefaction percentages for both categories 0 and 1, suggesting that it has a more balanced and accurate performance across the two categories. Concerning how accurate the models are, several performance criteria were used, and the results are shown in Table 3.

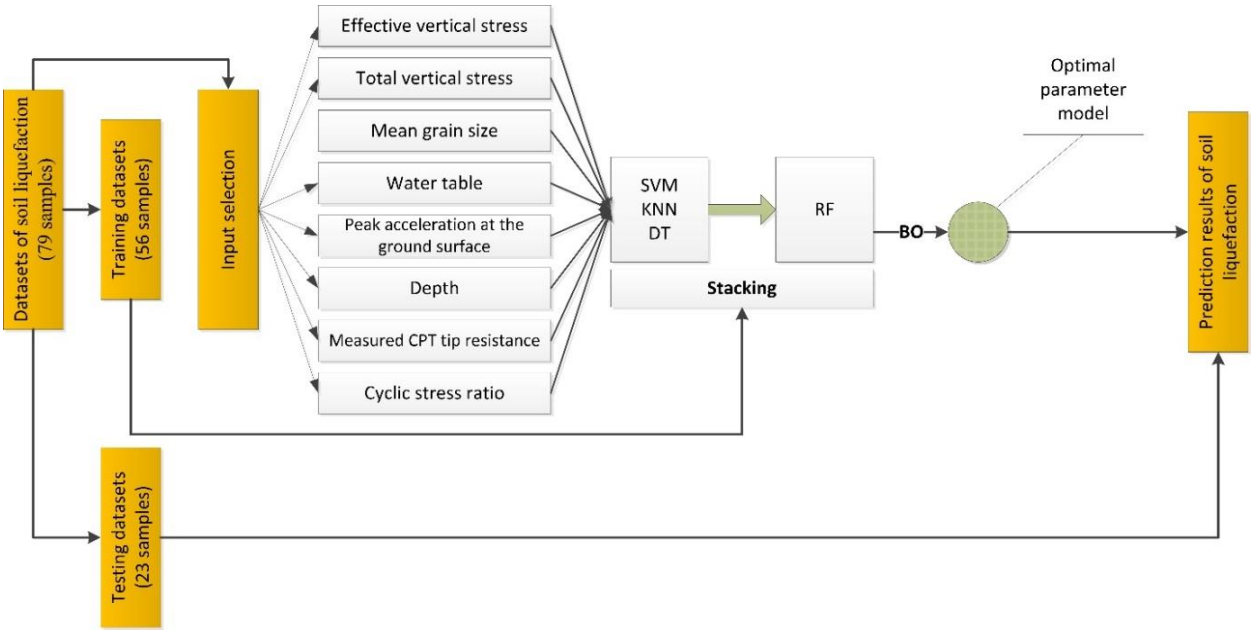


Fig. 3. Flowchart for predicting soil liquefaction.

Figure 5 presents a visual representation of the ranking system used to evaluate the performance of the models developed in this research. The heatmap shows the rankings of each model (Stacking, SVM, DT, and KNN) across various performance criteria (AUC, CA, F1, Precision, Recall) in both the training and testing phases. The color scale on the right indicates the ranking values, with darker shades representing higher rankings and lighter shades representing lower rankings.

The models built for this research were objectively and systematically evaluated using a simple ranking system. For each phase of the models' development and for each criterion, the best model receives the ranking four (because four models are developed) and the worst model receive ranking one. If two or more models show a similar performance a same ranking are assigned to them. The formula of the calculation of the accumulated ranking for each model is shown in equation 2.

$$Accumulative\ ranking = \sum_{i=1}^{5} \alpha_i + \sum_{j=1}^{5} \beta_j \quad (2)$$

where α_i is the performance criterion in the training phase, and β_j is the performance criterion in the testing phase. *i*/*j*: 1: AUC, 2: CA, 3: F1, 4: precision, and 5: recall.

As seen in Figure 5, the Stacking model consistently receives the highest ranking (4) across all performance criteria in both the training and testing phases, indicating its superior performance. The SVM model ranks second, with mostly rankings of 3, followed by the DT model with rankings ranging from 1 to 4. The KNN model generally receives the lowest rankings, suggesting its relatively weaker performance compared to the other models.

The results of the analysis in Table 3 and Figure 5 show that, in most cases, the stacking model had better performance than other models. The best model among the single models was the SVM (accumulated raking = 24), followed by the DT (accumulated raking = 22). The worst

model, on the other hand, was the KNN model (accumulated raking = 20). The suggested BO-Stacking ensemble-learning model offers superior learning and generalization capabilities, as well as superior prediction accuracy, compared to the combined single model. Consequently, the BO-Stacking ensemble-learning model may serve as a benchmark for the development of an intelligent decision-control system for soil liquefaction. It is also superior to other approaches for measuring soil liquefaction.

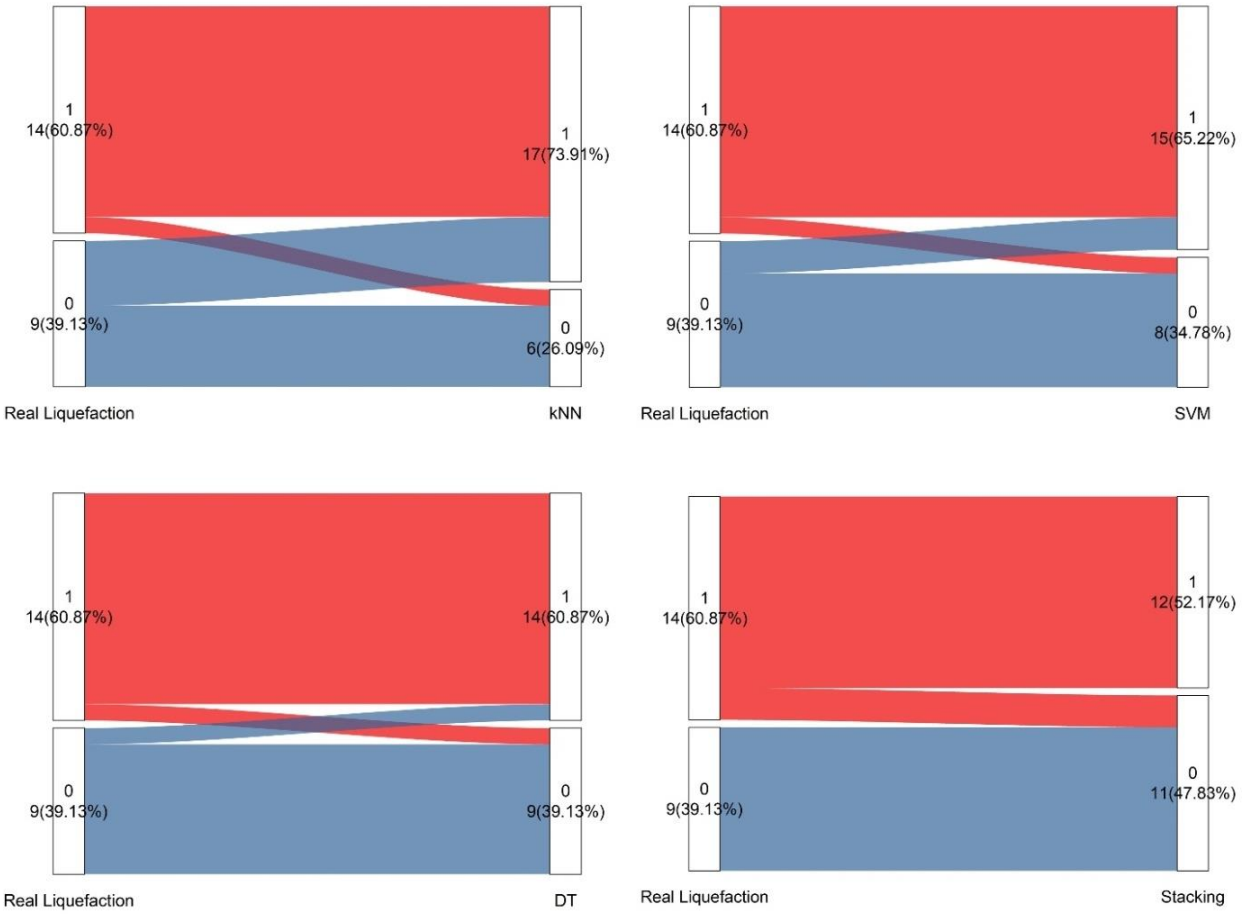


Fig. 4. Sneaky plots of the real and predicted soil liquefaction categories.

Table 3
Performance of the models developed in this study.

Model	TRAIN					TEST				
	AUC	CA	F1	Precision	Recall	AUC	CA	F1	Precision	Recall
KNN	0.857	0.839	0.821	0.844	0.839	0.921	0.783	0.771	0.792	0.783
DT	0.805	0.786	0.781	0.778	0.786	0.984	0.912	0.913	0.913	0.912
SVM	0.85	0.857	0.854	0.853	0.857	0.865	0.87	0.868	0.87	0.87
Stacking	0.95	0.875	0.87	0.872	0.875	0.992	0.913	0.914	0.929	0.913
Logistics regression	0.901	0.839	0.837	0.836	0.839	0.961	0.913	0.883	0.9	0.884

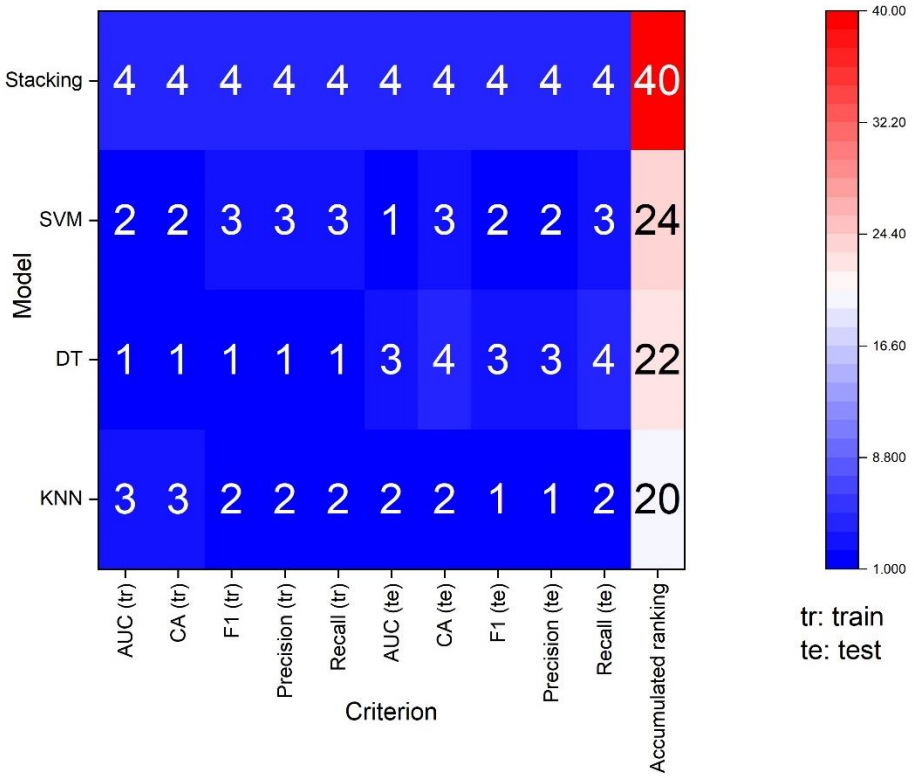
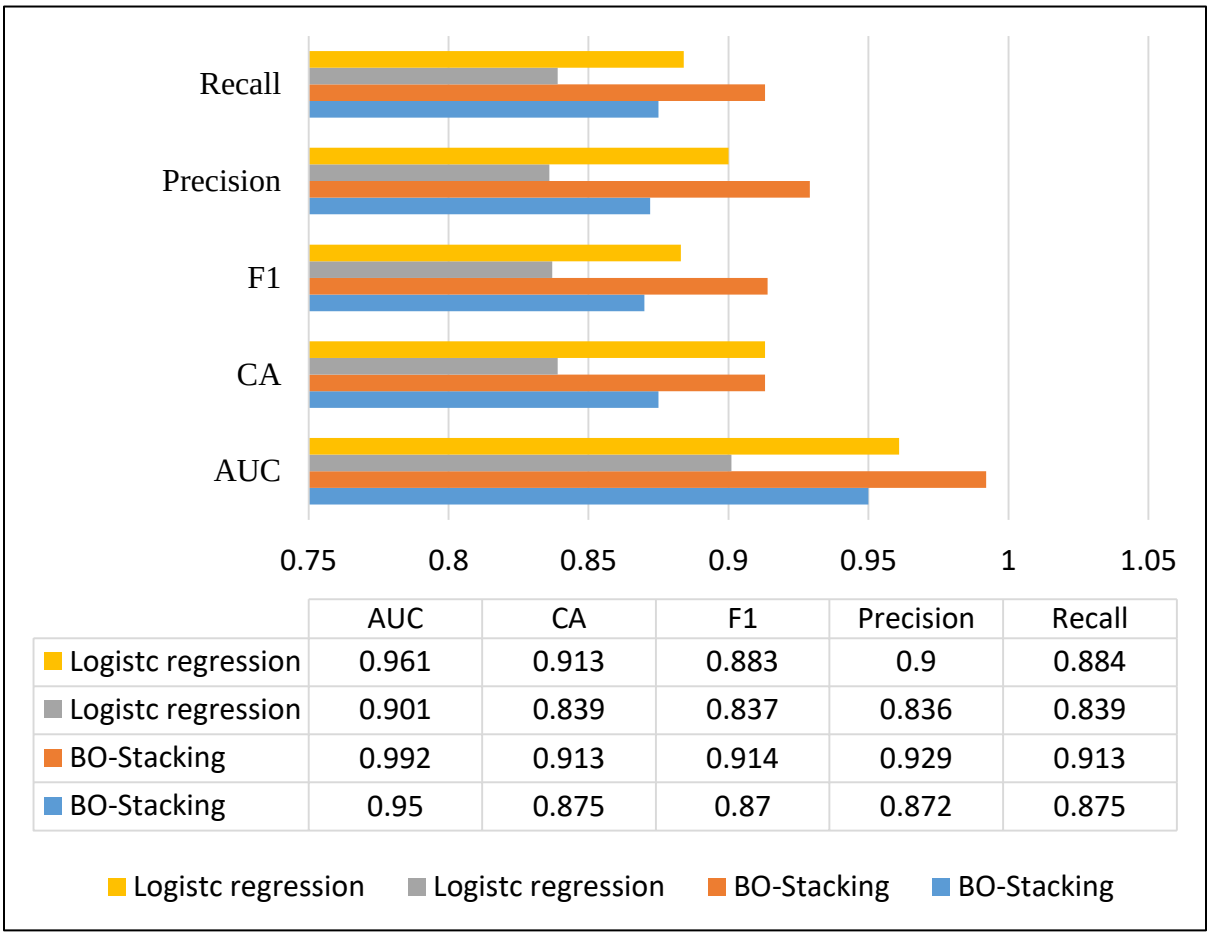


Fig. 5. Models' ranking.

Furthermore, a comparison was conducted between the performance of the BO-Stacking model and logistic regression (Figure 6). In comparing the findings of the BO-Stacking model and the logistic regression model for soil liquefaction forecasting, several key differences emerge. The BO-Stacking model consistently outperforms logistic regression across multiple evaluation metrics. The AUC values demonstrate the BO-Stacking model's superiority, with scores of 0.95 on the training set and an impressive 0.992 on the testing set, compared to logistic regression's lower scores of 0.901 and 0.961, respectively. Classification accuracy on the testing set is similar for both models at 0.913, but the BO-Stacking model achieves higher accuracy (0.875) on the training set compared to logistic regression (0.839). The F1-score, precision, and recall also favor the BO-Stacking model, indicating its stronger performance in capturing patterns and identifying positive instances. Overall, the findings demonstrate that the BO-Stacking model is more effective in accurately predicting soil liquefaction.

Our methodology, the BO-Stacking model, demonstrates its universality by offering a robust approach to accurately predicting soil liquefaction potential. By leveraging primary algorithms such as decision trees, support vector machines, and k-nearest neighbors, along with the secondary algorithm of random forest, our model integrates diverse techniques commonly used in the field of ML. This broadens the applicability of our approach across different scenarios and datasets. Moreover, the incorporation of Bayesian optimization enables the fine-tuning of hyperparameters for improved prediction accuracy. The use of the information gain technique for input selection further enhances the model's effectiveness. The results of our study showcase the superior performance of the BO-Stacking model, surpassing that of single prediction models.

With a testing accuracy of 0.913 and an AUC of 0.992, our model offers a viable and universal alternative for accurately predicting soil liquefaction. This study not only contributes to the existing literature but also provides practical implications for civil and structural project planning, ensuring better mitigation of earthquake-related risks.



	AUC	CA	F1	Precision	Recall
Logistc regression	0.961	0.913	0.883	0.9	0.884
Logistc regression	0.901	0.839	0.837	0.836	0.839
BO-Stacking	0.992	0.913	0.914	0.929	0.913
BO-Stacking	0.95	0.875	0.87	0.872	0.875

Fig. 6. Comparison between BO-Stacking model and logistic regression model.

These ML models used for this research offer a number of benefits over other methods, including: Typically, the KNN is employed for nonlinear regression, which is immune to outliers and accurate [95]. The DT is the fastest. In a short period of time, it may provide realistic and useful data-related outcomes [96]. When it comes to learning with little data, the SVM excels due to its high generalizability and its capacity to retain information [97]. Bayesian optimization uses the Gaussian process as its basis. In order to optimize the hyper-parameters, Bayesian optimization takes previous knowledge into account and offers the benefits of fewer iterations and a higher processing speed [98]. Therefore, the stacking ensemble-learning model adopts these strategies as its basis model and optimization strategy.

The results of this research are somewhat lower than those of a few prior soil liquefaction investigations that used distinct data sets. For instance, [55] and [28] obtained accuracy values of 92.2% and 93.1%, respectively, to forecast soil liquefaction using grey wolf optimization (GWO)-SVM and kernel Fisher discriminant analysis (KFDA) with least square support vector

machine (LSSVM) techniques. However, this outcome might be attributable to the number, kind, and quantity of inputs and outputs employed in these investigations. In other words, the accuracy of the constructed BO-stacking prediction model is satisfactory. This research advises that the BO-stacking model be employed and further developed to predict soil liquefaction in the future, particularly when single models do not provide the appropriate degree of precision.

4. Limitations and Future Works

While the BO-Stacking model has demonstrated superior performance in predicting soil liquefaction, it is essential to acknowledge the limitations of this study and discuss potential avenues for future research. One limitation of the current study is the reliance on a specific dataset with a limited range of soil conditions and geological settings. While the model has shown promising performance on the available data, its robustness to variations in dataset size, characteristics, and geological regions or earthquake scenarios remains an important consideration. The model's performance may vary when applied to datasets with significantly different soil characteristics, tectonic settings, or more extreme conditions than those represented in the training data. Furthermore, the size of the dataset can potentially impact the model's ability to capture the full range of variability and patterns present in different regions or scenarios. Therefore, future studies should focus on rigorously evaluating the BO-stacking model's robustness and transferability by validating its performance using diverse datasets representing a wider range of soil liquefaction scenarios, geological regions, and earthquake characteristics. This can involve techniques such as cross-validation, transfer learning, domain adaptation, and ensemble methods to enhance the model's generalization capabilities and ensure reliable performance across varying conditions.

Another limitation is the number of input features used in the model. Although the information gain method was employed to select the most relevant features, incorporating additional relevant features could potentially enhance the model's predictive capabilities. Future research should explore the inclusion of more data samples and features in the experimental database to further improve the accuracy of the BO-Stacking model.

Another avenue for future research is to explore the integration of additional machine learning techniques or algorithms into the BO-stacking model framework. While the current implementation combines decision trees, support vector machines, k-nearest neighbors, and random forests, the model's predictive capabilities could potentially be further enhanced by incorporating other state-of-the-art machine learning algorithms. Techniques such as deep learning, gradient boosting, or ensemble methods like stacking and blending could be investigated and integrated into the BO-stacking model. By leveraging the strengths and diverse approaches of multiple machine learning algorithms, the model may be able to capture more complex patterns and relationships within the data, leading to improved accuracy in predicting soil liquefaction potential. However, careful consideration must be given to the computational complexity and resource requirements of integrating additional algorithms, as well as potential issues such as overfitting or increased model complexity. Nonetheless, exploring the combination of the BO-stacking model with other advanced machine learning techniques

presents an intriguing opportunity to push the boundaries of predictive performance in this domain.

Moreover, while the BO-Stacking model has shown promising results, it is crucial to emphasize that it should only be employed under similar conditions and with a reasonable range of data. Extrapolating the model's performance beyond the scope of the studied conditions may lead to uncertainties and inaccuracies. Future research should focus on defining the boundaries and limitations of the model's applicability to ensure its reliable use in practice.

5. Conclusions

Using the characteristics of existing soil liquefaction datasets, this research developed a stacked ensemble-learning model with Bayesian optimization to forecast soil liquefaction. This study's models were created utilizing six inputs and a single output, soil liquefaction. Prior to the development of these models, a method of information gain was used for input inclusion. The nine potential inputs were reduced to five that were finally used. Furthermore, the BO-Stacking model's advantages are determined by comparing the single learner to the stacked ensemble-learning model and the BO method. Here are the key findings of our study: (1) We leverage the automated parameter searching capability of the BO method to enhance the hyperparameters of the ML model, effectively mitigating the challenges of overfitting or underfitting. (2) By applying the optimized model, the stacking ensemble approach is employed, resulting in further improvements in the accuracy of the model. Moreover, in the test datasets, the accuracy of forecasting soil liquefaction is 0.913, demonstrating that this technique can reliably forecast soil liquefaction to decrease earthquake-related risks.

The practical application of the results of our research is highly relevant in the field of civil and structural project planning. The accurate prediction of soil liquefaction potential plays a crucial role in mitigating the risks associated with liquefaction during earthquakes. By introducing the BO-Stacking model, we provide a powerful tool for practitioners to improve their forecasting capabilities. The model's superior performance demonstrates its reliability in predicting soil liquefaction. Incorporating this model into practice enables more informed decision-making and the development of appropriate strategies to design and construct resilient infrastructure in areas prone to liquefaction. Ultimately, our research contributes to safer civil and structural projects by equipping professionals with a practical solution for assessing and addressing the potential risks of soil liquefaction.

The BO-stacking model might be used in future studies to forecast soil liquefaction. The need for more data and studies on soil liquefaction in more severe circumstances should be underlined. The hybrid model provided here should only be employed under similar conditions and with a reasonable range of data. To increase the accuracy of the BO-stacking model, it is suggested that additional data samples and features be added to the experimental database in the future.

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Conflicts of interest

The authors declare no conflict of interest.

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