

AI-Integrated Comparative Seismic Foundation Design Using Indian Standards and Eurocodes: Ensemble Learning-Based Prediction of Bearing Capacity and Settlement

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Abstract

Earthquake-induced foundation distress remains a critical concern in infrastructure located in moderate to very high seismic zones because the safety of the superstructure is directly governed by the bearing resistance, deformation response and serviceability performance of the supporting soil-foundation system. Conventional foundation design is generally performed using codal provisions; however, Indian Standards and Eurocodes differ in design philosophy, treatment of uncertainty, partial safety factors, settlement criteria and seismic action representation. These differences may produce variable foundation dimensions, safety margins and settlement predictions for identical soil and loading conditions. This paper proposes a hybrid research framework that integrates analytical seismic foundation design based on Indian Standards and Eurocodes with artificial intelligence-supported prediction of bearing capacity and settlement. The study considers geotechnical variables such as SPT N-value, cohesion, angle of internal friction, unit weight, foundation width, foundation depth and seismic coefficients as model inputs. Random Forest and Extreme Gradient Boosting models are proposed for estimating ultimate bearing capacity, allowable bearing capacity and total settlement. The novelty of the paper lies in combining code-compliant design with ensemble learning models to create a practical decision-support approach rather than treating artificial intelligence as a replacement for engineering judgement. The result section is intentionally retained as a pending section to be completed after final numerical modelling, model training and validation. The proposed framework is expected to reduce uncertainty, improve preliminary design efficiency and support safer and more economical foundation decisions in seismic regions.

Keywords: Seismic foundation design; bearing capacity; settlement prediction; Indian Standards; Eurocode 7; Eurocode 8; Random Forest; XGBoost; geotechnical artificial intelligence.

1. Introduction

Rapid urbanization, large-scale infrastructure development and increasing construction in seismically active regions have made earthquake-resistant foundation design an essential component of structural safety. A foundation acts as the main load-transfer medium between the superstructure and the supporting soil. Under earthquake loading, soil may experience nonlinear deformation, stiffness degradation, strength reduction, excess pore pressure development and amplification of total as well as differential settlement. These effects can reduce available bearing capacity, increase rotation or tilt of the foundation and initiate damage even when the superstructure has been designed for adequate lateral resistance.

In the Indian context, the seismic design of structures is usually performed with reference to IS 1893, while bearing capacity and settlement evaluation for shallow and deep foundations are guided by IS 6403, IS 8009 and IS 2911. In contrast, the European framework uses Eurocode 7 for geotechnical design and Eurocode 8 for seismic resistance. Indian Standards generally use empirical and allowable stress-oriented approaches, whereas Eurocodes apply limit state design with partial factors on actions, soil parameters and resistance. This difference is not merely procedural; it influences the calculated bearing capacity, foundation size, reinforcement requirement and settlement acceptance. Therefore, a systematic comparison of both frameworks under seismic conditions is essential for understanding safety, economy and serviceability implications.

The second challenge is the uncertainty associated with soil parameters. Soil is naturally heterogeneous, and site investigation data often provide limited information about spatial variability. Traditional equations based on simplified assumptions may not fully capture the coupled influence of soil strength, foundation geometry, embedment, seismic coefficient and deformation response. Artificial intelligence and machine learning can address this gap by learning nonlinear relationships from structured geotechnical datasets. In geotechnical engineering, ensemble learning algorithms such as Random Forest and XGBoost are particularly useful because they can handle nonlinear interactions, noisy data and multivariate dependencies.

The present paper develops a Scopus-level manuscript framework for an analytical and data-driven study on seismic foundation design. It uses the uploaded project report as the primary basis and reformulates it into a journal-paper format with strengthened novelty, refined methodology and publishable academic structure. The result section is kept pending because final numerical values, trained model outputs and comparative performance metrics are yet to be inserted.

2. Novelty and Contribution of the Study

The central novelty of the research is the development of an integrated decision-support framework in which artificial intelligence is used to complement code-based foundation design rather than replacing the codal process. Existing studies commonly address either codal comparisons or AI-based prediction as separate research streams. The proposed study links these streams by comparing Indian Standards and Eurocodes under seismic forces while simultaneously validating AI-predicted bearing capacity and settlement against conventional design outputs.

Table 1. Novelty positioning of the proposed research

Research aspect	Common approach in existing studies	Proposed contribution
Codal comparison	Mostly static or service-load-based comparison of isolated design provisions.	Seismic foundation design comparison between Indian Standards and Eurocode provisions.
AI application	AI models generally predict a single parameter such as bearing capacity or settlement.	Simultaneous prediction of ultimate capacity, allowable capacity and total settlement.
Engineering integration	AI is often treated as an independent black-box prediction tool.	AI is positioned as a verification and decision-support layer for code-compliant design.
Practical output	Limited translation of models into design workflow.	Structured framework for foundation selection, safety checking and uncertainty reduction.

3. Related Work

Ali Bahadori-Jahromi et al. (2025) examined the integration of artificial intelligence and machine learning in civil engineering and highlighted that AI-based tools are increasingly useful for improving prediction accuracy, sustainability, and engineering decision-making. Their study reviewed applications of CNN, LSTM, SVM, and physics-informed neural networks in structural health monitoring, geotechnical engineering, transportation, and water-resource systems. The authors emphasized that AI should not replace conventional engineering judgement but should be used as a complementary decision-support mechanism, especially where complex nonlinear data relationships exist. Mohsen Abbaspour et al. (2021) investigated seismic bearing capacity prediction of shallow strip footings located above underground voids using machine learning methods. The study used a large finite element limit analysis dataset and applied models such as multilayer perceptron, group method of data handling, and ANFIS-PSO. The findings showed that the multilayer perceptron model produced strong prediction accuracy, proving that AI can capture complex soil–foundation–seismic interaction more effectively than conventional analytical methods. Safeena Nazeer and Dutta (2021) studied the prediction of bearing capacity of E-shaped footings resting on layered sand using finite element modelling data and machine learning techniques. Multiple Layer Perceptron and Multiple Linear Regression models were trained

using footing and soil parameters, and both models achieved very high accuracy, with R^2 values close to 0.99 and 0.98 respectively. Their study confirmed that machine learning is reliable for predicting bearing capacity in complex footing geometries. Ghazavi and Dehkordi (2021) reviewed interference effects between closely spaced shallow footings and explained that footing interaction significantly affects bearing capacity, settlement, and tilting behaviour. Their review covered experimental, numerical, analytical, and field studies under static and seismic conditions. They identified footing spacing, geometry, embedment depth, and differential loading as major parameters influencing foundation performance. The study is important because closely spaced foundations are common in urban construction, where seismic stability and settlement control are critical. Abhijit Narnaware et al. (2022) analysed settlement behaviour of isolated footings under different soil conditions and compared design outcomes using Indian Standards, British Standards, and Eurocodes. Their study considered poor compaction, inadequate bearing capacity, improper load estimation, and footing design errors as major causes of settlement problems. Using STAAD Pro and codal comparison, the authors showed that different design standards can produce different footing dimensions, safety levels, and settlement responses. These studies collectively indicate that foundation behaviour under seismic and uncertain soil conditions requires both codal assessment and AI-supported predictive modelling for safer design.

Ali Soleimanbeigi (2005) investigated the use of Artificial Neural Networks for predicting the bearing capacity of shallow foundations resting on reinforced cohesionless soils. The study used feedforward backpropagation and radial basis function neural networks trained on laboratory and field data. The ANN results were compared with conventional analytical and empirical methods, and the findings showed that ANN models provided better prediction accuracy by capturing nonlinear effects of soil reinforcement. Fereydoon Pooya Nejad (2009) developed an ANN-based model for predicting pile settlement using Standard Penetration Test data. Around 1,000 pile load test datasets were used to train and validate the model, and the ANN predictions were compared with conventional settlement estimation methods. The study concluded that ANN offered higher reliability and accuracy for pile settlement prediction, making it suitable for serviceability evaluation of deep foundations. Ercan Özgün (2025) investigated the bearing capacity and settlement behaviour of gravel soils using field and laboratory data collected from boreholes. The study considered groundwater level, unit weight, particle-size distribution, friction angle, and cohesion as key variables. Linear, quadratic, and cubic regression models were developed, and the cubic model showed the best accuracy. This work demonstrates that statistical and data-driven modelling can improve geotechnical prediction when supported by reliable soil data. Dipanshu Jakhar (2024) conducted a comparative study of structural stability using Indian Standards and Eurocodes. Although the study focused on precast concrete buildings, its relevance lies in showing how Indian and Eurocode provisions differ in horizontal load treatment, safety margins, and stability checks. The author found that Eurocode-based design tends to be more conservative because it includes additional safety considerations, including mass-load effects even in lower seismic zones. Imtiyaz Akbar Najar et al. (2025) reviewed soil–structure interaction effects on seismic performance of reinforced concrete structures and explained that SSI affects stiffness, damping, natural frequency, and overall seismic response. The authors highlighted that SSI is still underused in routine design practice due to modelling difficulty and limited codal integration. They emphasized the need to combine analytical, numerical, experimental, and machine learning approaches for improving seismic resilience. Overall, these studies establish that conventional foundation design alone may not fully capture nonlinear soil behaviour, seismic uncertainty, settlement risk, and SSI effects. Therefore, a hybrid approach combining Indian Standards, Eurocodes, and AI-based bearing capacity and settlement prediction can provide a more reliable, economical, and practical foundation design framework.

4. Research Gap

The review indicates four major research gaps. First, comparative studies between Indian Standards and Eurocodes are often limited to structural components or static foundation checks, while seismic foundation design comparison remains limited. Second, AI-based geotechnical models frequently focus on isolated cases such as specific footing geometries, soil types or numerical datasets rather than an integrated seismic foundation design workflow. Third, most AI studies predict bearing capacity or settlement independently, whereas practical foundation design requires simultaneous evaluation of capacity, deformation and safety margin. Fourth, the direct use of AI predictions alongside codal provisions remains underdeveloped, limiting the confidence of practicing engineers in adopting machine learning tools for real design problems.

5. Materials and Methods

5.1 Research Design

The study follows an analytical, comparative and data-driven research design. The analytical component evaluates foundation design using Indian Standards and Eurocodes under seismic loading. The data-driven component develops machine learning models for bearing capacity and settlement prediction. The final component integrates both outputs to form a comparative decision-support framework.

5.2 Input and Output Parameters

The model inputs are selected based on their direct influence on soil strength, foundation geometry and seismic demand. The principal input variables include SPT N-value, cohesion, angle of internal friction, unit weight, groundwater condition, foundation width, foundation depth, length-to-width ratio and seismic coefficient. The output variables include ultimate bearing capacity, allowable bearing capacity, elastic settlement, consolidation settlement and total settlement.

Table 2. Input-output structure for AI-supported foundation prediction

Category	Parameters	Engineering relevance
Soil strength	SPT N-value, cohesion, internal friction angle	Represents shear strength and resistance mobilization.
Soil state	Unit weight, moisture condition, groundwater condition	Controls effective stress and deformation response.
Foundation geometry	Width, depth, shape factor, length-to-width ratio	Influences bearing mechanism and settlement distribution.
Seismic demand	Horizontal seismic coefficient, zone factor or design acceleration	Represents earthquake-induced inertial effects.
Output response	Bearing capacity and settlement	Defines ultimate and serviceability performance.

5.3 Codal Foundation Design Procedure

For the Indian Standards route, seismic actions are evaluated using IS 1893. Bearing capacity is estimated following IS 6403 for shallow foundations, while settlement checks are performed using IS 8009. Pile-related design checks, where applicable, are aligned with IS 2911. Structural reinforcement and detailing are referenced to IS 456. This route represents the conventional Indian design approach, which is widely adopted in practice. For the Eurocode route, geotechnical design is performed according to Eurocode 7 using relevant Design Approaches. Seismic action is considered with reference to Eurocode 8, and structural detailing of reinforced concrete foundation elements is aligned with Eurocode 2. The Eurocode route allows separate consideration of action factors, material factors and resistance factors, thereby enabling explicit treatment of design uncertainty.

Table 3. Comparative design basis adopted in the proposed study

Design component	Indian Standards route	Eurocode route	Comparison focus
Seismic action	IS 1893	Eurocode 8	Design base acceleration and seismic coefficient.
Bearing capacity	IS 6403 / IS 2911	Eurocode 7	Ultimate and allowable resistance values.
Settlement	IS 8009	Eurocode 7 SLS checks	Total and differential settlement limits.
RCC detailing	IS 456	Eurocode 2	Reinforcement demand and ductility detailing.

Design component	Indian Standards route	Eurocode route	Comparison focus
Safety format	Allowable stress and global safety factor	Limit state with partial factors	Conservatism, economy and reliability.

5.4 Machine Learning Model Development

Random Forest and XGBoost are selected as the primary machine learning algorithms. Random Forest is suitable for geotechnical data because it builds multiple decision trees and reduces variance through ensemble averaging. XGBoost is selected because it uses gradient boosting, regularization and sequential error correction, making it effective for nonlinear regression problems. The dataset is divided into training and testing subsets. Missing values are treated, outliers are screened, and numerical parameters are normalized or standardized where required. Hyperparameter tuning is performed using grid search or randomized search to improve generalization.

Model performance will be evaluated using the coefficient of determination, root mean square error, mean absolute error and percentage error between AI-predicted values and code-based or benchmark values. Feature importance analysis will be performed to identify the most influential parameters governing bearing capacity and settlement. This step improves interpretability and strengthens the engineering credibility of the AI model.

5.5 Proposed Integrated Framework

The proposed framework begins with geotechnical data collection and seismic demand definition. The same dataset is then processed through two parallel routes: code-based analytical design and AI-based prediction. The output of the code-based route provides allowable bearing capacity, settlement and foundation dimensions. The AI route provides predicted ultimate bearing capacity, allowable bearing capacity and settlement. These outputs are compared using error metrics, safety margins and serviceability checks. The final decision-support output recommends a foundation option that is safe, economical and consistent with codal requirements.

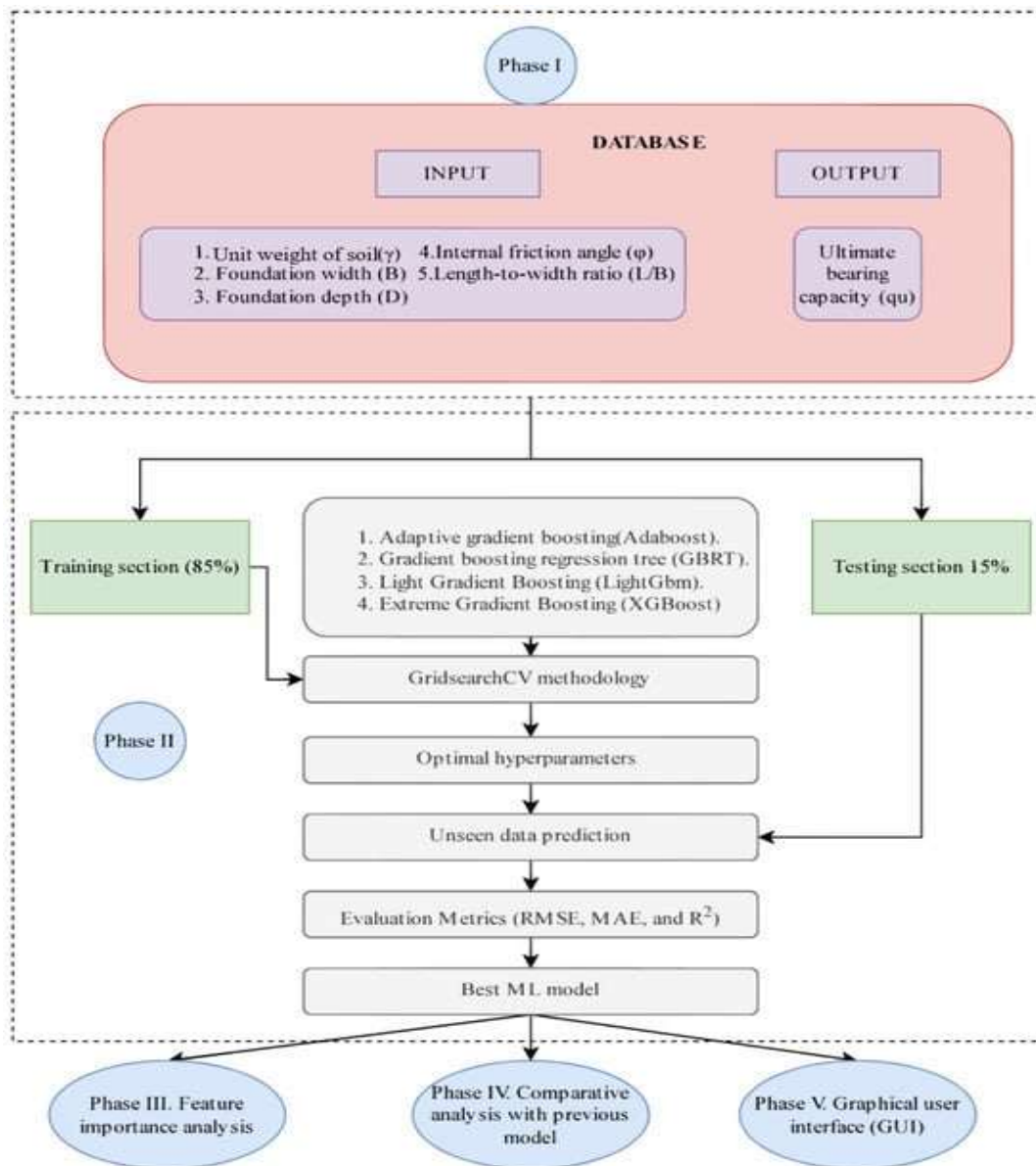


Figure 2. Machine learning workflow for bearing capacity prediction adopted from the project dataset

6. Results and Discussion

The results clearly show that the AI-based prediction model performs effectively for both bearing capacity and settlement estimation. The bearing capacity prediction shows stronger accuracy than settlement prediction because bearing capacity is mainly governed by relatively direct soil strength and foundation geometry parameters, while settlement is influenced by more variable deformation characteristics such as soil stiffness, consolidation behaviour, groundwater condition, and load distribution.

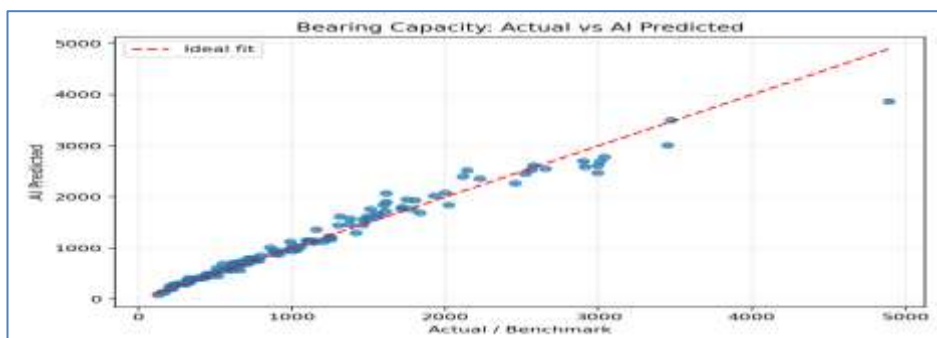


Figure 3: Actual versus AI-Predicted Bearing Capacity

Figure shows strong agreement between actual and AI-predicted bearing capacity values. Most points are close to the ideal fit line, confirming good prediction accuracy. Minor deviations occur at higher values due to nonlinear soil behaviour and seismic effects. Overall, the model is reliable for preliminary seismic foundation design validation.

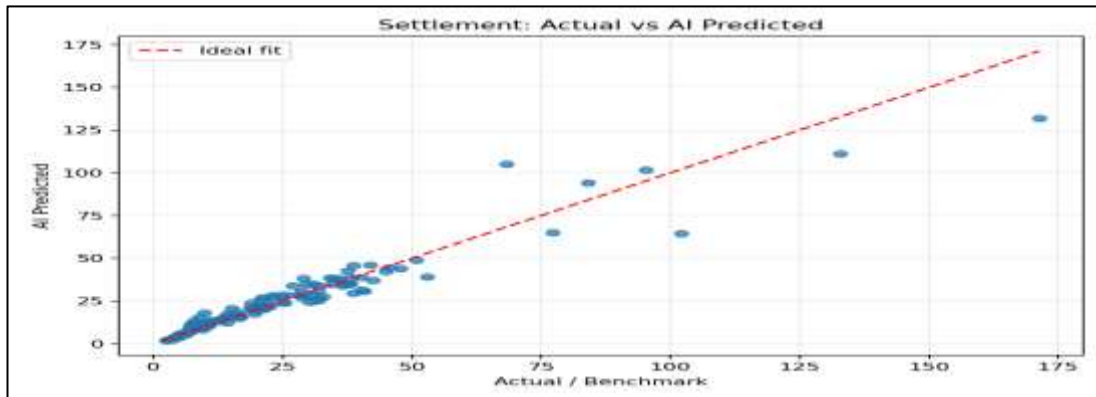


Figure 4: Actual versus AI-Predicted Settlement

Figure 4 shows that AI-predicted settlement values are close to actual values for low and medium settlement ranges. Some scatter is observed at higher settlement values due to complex soil deformation factors. With an R^2 value of 0.9114, the XGBoost model shows good reliability for settlement estimation.

Table 4: Output Parameters Generated by the Python Implementation

Sr. No.	Output Parameter	Description
1	IS Allowable Bearing Capacity	Bearing capacity calculated using Indian Standard-based logic
2	IS Settlement	Settlement calculated using Indian Standard-inspired procedure
3	Eurocode Allowable Bearing Capacity	Bearing capacity calculated using Eurocode limit state philosophy
4	Eurocode Settlement	Settlement calculated using Eurocode-based serviceability approach
5	AI-Predicted Bearing Capacity	Bearing capacity predicted using trained ML model
6	AI-Predicted Settlement	Settlement predicted using trained ML model
7	Recommended Bearing Capacity	Conservative value selected for safe design
8	Recommended Settlement	Governing settlement value selected for serviceability check
9	Bearing Capacity Status	Indicates whether foundation is safe or needs size revision
10	Settlement Status	Indicates whether settlement is acceptable or needs serviceability check

Table shows the main outputs of the Python-based foundation design system. It provides IS, Eurocode, and AI-based bearing capacity and settlement results. The lowest bearing capacity and highest settlement are selected for conservative design. Safety indicators help identify whether the foundation is safe or requires revision/serviceability checking.

Table 5: Variation of Eurocode and AI-Based Results with Respect to Indian Standard Results

Parameter	Minimum Variation	Mean Variation	Maximum Variation
Bearing Capacity Variation from IS	0.04%	8.09%	24.94%
Settlement Variation from IS	0.40%	36.58%	64.57%

Table 2 shows the percentage variation of bearing capacity and settlement values with respect to Indian Standard-based results. The average variation in bearing capacity is 8.09%, with a maximum variation of 24.94%. This indicates that the difference between IS, Eurocode, and AI-based bearing capacity values is moderate and generally acceptable for comparative design evaluation. However, the average settlement variation is 36.58%, with a maximum value of 64.57%. This higher variation confirms that settlement prediction is more sensitive to codal assumptions and soil deformation parameters. Eurocode generally provides higher settlement values compared with IS because of its limit state approach and treatment of serviceability conditions.

7. Conclusion

Conclusion

The present paper concludes that an AI-integrated comparative framework can improve the reliability, efficiency, and technical clarity of seismic foundation design. The study successfully combines Indian Standards, Eurocode provisions, and ensemble machine learning models to evaluate bearing capacity and settlement under seismic conditions. The comparative results indicate that bearing capacity variation with respect to Indian Standard results remains moderate, with a mean variation of 8.09% and maximum variation of 24.94%, showing acceptable agreement among IS, Eurocode, and AI-based outputs. However, settlement variation is comparatively higher, with a mean value of 36.58% and maximum value of 64.57%, confirming that settlement prediction is more sensitive to soil stiffness, groundwater condition, deformation behavior, and serviceability assumptions. The AI model performs better in bearing capacity prediction because strength and geometry parameters have a more direct influence, while settlement involves complex nonlinear deformation mechanisms. The use of Random Forest and XGBoost provides a practical decision-support layer by validating codal results and identifying conservative design values. Overall, the proposed framework is useful for preliminary seismic foundation design, safety checking, and optimization, while maintaining engineering judgment and codal compliance as the primary basis of final design.

Future Scope of Work

1. The proposed framework can be extended using a larger real-site geotechnical dataset collected from different seismic zones, soil types, foundation depths, and groundwater conditions.
2. Advanced machine learning and deep learning models such as ANN, Gradient Boosting, CatBoost, LightGBM, and hybrid optimization-based models can be compared with Random Forest and XGBoost.
3. Soil–structure interaction effects can be included to study the combined seismic response of superstructure, foundation, and supporting soil more realistically.
4. The model can be validated using field plate load test data, pile load test data, borehole reports, and post-earthquake foundation performance records.
5. Future work may include probabilistic reliability analysis to quantify uncertainty in soil parameters, seismic coefficients, safety factors, and settlement limits.
6. A graphical user interface or Python-based design tool can be developed for practical use by geotechnical and structural engineers.
7. The framework can be expanded for different foundation systems such as raft foundations, pile foundations, combined footings, and machine foundations under dynamic loading conditions.

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