

CROSS-REGIONAL EARTHQUAKE-INDUCED SOIL LIQUEFACTION ASSESSMENT USING A MECHANISM-INFORMED EXPLAINABLE AI-DRIVEN DEEP LEARNING FRAMEWORK

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ABSTRACT

Accurate assessment of earthquake-induced soil liquefaction is challenging due to nonlinear interactions among seismic loading, soil properties, and groundwater conditions. This study proposes a physics-informed and explainable hybrid deep learning framework for reliable liquefaction prediction across multiple seismic regions. Classical geotechnical parameters, including cyclic stress ratio (CSR), cyclic resistance ratio (CRR), and factor of safety (FS), are embedded into a constrained learning formulation to ensure physical consistency. A 1D-CNN-BiLSTM-attention architecture captures localized and depth-wise dependencies, while SHAP and sensitivity analyses enhance interpretability. Cross-regional validation demonstrates strong generalization capability and improved predictive performance compared to conventional machine learning approaches.

Keywords: *Cyclic Stress Ratio (CSR), Cyclic Resistance Ratio (CRR), Factor Of Safety (FS), Soil Liquefaction, Classical Geotechnical Parameters, Cross-Regional Validation.*

1. INTRODUCTION

Earthquake-induced soil liquefaction is a major geotechnical hazard responsible for severe ground deformation and infrastructure damage during strong seismic events. Foundational work by Seed and Idriss [22] established the simplified cyclic stress ratio-cyclic resistance ratio (CSR-CRR) framework for liquefaction evaluation, which was later refined through workshop recommendations and updated triggering procedures [19,21]. Shear-wave velocity-based

approaches further expanded empirical assessment techniques [20,24], and practical implementation has been supported by national guidelines such as NIST/NEHRP [23]. Although these classical methods remain widely applied, they depend on empirical correlations that may not fully capture complex nonlinear interactions among seismic loading, soil stratification, and groundwater conditions.

The increasing availability of case-history databases has motivated the application of machine

learning techniques to liquefaction susceptibility prediction. Early studies demonstrated the feasibility of artificial intelligence in this domain [18], and subsequent investigations employed ANN, ensemble learning, and boosting algorithms to improve predictive accuracy [3,12,17,25]. Comprehensive reviews highlight rapid advancements in data-driven liquefaction modeling over the past decade [13,14]. More recently, deep learning architectures—including CNN, LSTM, and hybrid models—have shown superior performance in modeling nonlinear geotechnical systems [1,4,5,15,16], with emerging efforts toward explainability and feature attribution [2,9,11].

Despite these developments, challenges remain regarding physical consistency and cross-regional generalization. This study addresses these gaps by integrating physics-informed constraints with an explainable hybrid deep learning framework for robust, multi-regional liquefaction assessment.

Research Questions and Hypotheses

Research Question 1 (RQ1):

Can physics-informed constraints improve liquefaction prediction accuracy compared with purely data-driven machine learning and deep learning approaches?

Research Question 2 (RQ2):

Can explainable AI techniques such as SHAP and attention mechanisms provide meaningful interpretation of liquefaction prediction outcomes?

Research Question 3 (RQ3):

Can the proposed framework maintain robust performance across different seismic regions and geological environments?

Hypotheses

H1: Physics-informed learning significantly improves predictive accuracy and physical consistency.

H2: Explainability mechanisms enhance transparency and trustworthiness of model predictions.

H3: Cross-regional validation demonstrates strong generalization capability of the proposed framework.

Study Design and Research Protocol

The present study follows a structured research methodology consisting of six major phases: (1) multi-event dataset collection from historical earthquake case histories, (2) preprocessing and feature engineering, (3) computation of physics-based parameters including CSR, CRR, and FS, (4) development of the proposed Physics-Informed CNN-BiLSTM-Attention model, (5) explainability analysis using SHAP and attention visualization, and (6) cross-regional validation and performance assessment. This protocol ensures methodological transparency, reproducibility, and scientific rigor throughout the study.

2. RESEARCH GAP AND CONTRIBUTIONS

2.1 Research Gap

Despite significant progress in liquefaction assessment methodologies, several limitations remain in current research. Classical empirical frameworks based on CSR–CRR relationships [19,21,22] and shear-wave velocity correlations [20,24] provide reliable engineering guidance but rely on simplified deterministic formulations. These methods may not fully represent the highly nonlinear and coupled interactions among seismic intensity, soil properties, and groundwater conditions.

Recent machine learning studies have improved predictive accuracy by leveraging large case-history datasets [3,12,17,25], and comprehensive reviews confirm rapid methodological advancements in this domain [13,14]. Deep learning architectures such as CNN, LSTM, and hybrid models have demonstrated enhanced capability in modeling nonlinear geotechnical behavior [1,4,5,15,16]. However, three critical research gaps remain:

- 1. Lack of Physics Integration:** Most deep learning models operate purely as data-driven black-box systems without embedding established geotechnical theory (e.g., CSR, CRR, FS relationships), which may result in physically inconsistent predictions.
- 2. Limited Interpretability:** Although recent studies have introduced feature importance analysis using SHAP or permutation techniques [2,9,11], systematic integration of explainability within deep architectures for liquefaction assessment remains insufficient.

3. Insufficient Cross-Regional Validation:

Many existing models are validated within single regional datasets, raising concerns regarding generalization across different seismic and geological environments.

2.2 Related work

Research on earthquake-induced soil liquefaction assessment has evolved from empirical formulations to advanced data-driven modeling approaches. Early developments were grounded in simplified cyclic stress ratio–cyclic resistance ratio (CSR–CRR) concepts introduced by Seed and Idriss [22]. These formulations provided a practical framework for evaluating liquefaction triggering based on in-situ test data. Subsequent refinements and workshop recommendations consolidated standardized procedures for SPT- and CPT-based liquefaction evaluation [19,21]. Shear-wave velocity–based correlations further expanded assessment methodologies by incorporating dynamic soil properties [20,24], while national guidelines such as NIST/NEHRP [23] translated these principles into engineering practice.

With the growth of liquefaction case-history databases, machine learning techniques were introduced to enhance predictive capability. Early applications demonstrated that artificial neural networks could effectively model nonlinear relationships among geotechnical parameters [18]. Later studies applied ensemble learning, support vector machines, and boosting algorithms to improve classification accuracy and reduce uncertainty [3,12,17,25]. Comprehensive reviews have documented the rapid expansion of machine learning applications in liquefaction susceptibility modeling over recent decades [13,14].

More recently, deep learning architectures have gained prominence due to their superior representation learning capacity. Convolution neural networks (CNN) and recurrent neural networks (RNN), including long short-term memory (LSTM) models, have been applied to capture complex nonlinear interactions and sequential soil-layer dependencies [15,16]. Hybrid deep architectures combining convolution and recurrent components have shown improved performance in geotechnical stability problems [5]. Large-scale investigations report advancements in deep learning-based liquefaction mapping and susceptibility prediction [1,4,6]. Additionally, emerging research emphasizes explainable artificial

intelligence through SHAP-based feature attribution and permutation importance analysis [2,9,11].

Despite these advancements, most existing models remain purely data-driven, with limited integration of geotechnical theory and insufficient cross-regional validation. This highlights the need for physics-informed and interpretable deep learning frameworks capable of providing reliable and generalizable liquefaction assessment.

3. ARCHITECTURE OF THE PROPOSED PHYSICS-INFORMED HYBRID FRAMEWORK

As illustrated in Figure 4, the proposed framework establishes a unified integration of geotechnical theory and advanced deep learning to achieve physically consistent, interpretable, and generalizable liquefaction prediction. The architecture is organized into sequential computational stages, each designed to address limitations of purely empirical or purely data-driven approaches.

3.1 Multi-Event Dataset Compilation

A comprehensive liquefaction case-history database was assembled from multiple major seismic events, including Kobe (1995), Chi-Chi (1999), Bhuj (2001), and Tohoku (2011). The compiled dataset encompasses seismic intensity indicators, in-situ soil testing parameters, stress-state variables, and hydrogeological conditions. This multi-source integration ensures heterogeneity in soil types, seismic loading patterns, and geological settings, thereby improving the model's capability to generalize across diverse tectonic environments.

3.2 Data Preprocessing and Physically Consistent Feature Engineering

To enhance training stability and predictive robustness, a structured preprocessing pipeline was implemented. Missing observations were statistically imputed to preserve dataset completeness. Class imbalance was mitigated using Synthetic Minority Over-Sampling Technique (SMOTE), reducing bias toward non-liquefaction cases. All continuous variables were normalized to ensure numerical stability during optimization. Beyond raw features, physics-driven variables—including Cyclic Stress Ratio (CSR), Cyclic

Resistance Ratio (CRR), and Factor of Safety (FS)—were computed using established soil mechanics formulations. The inclusion of these parameters embeds mechanistic understanding directly into the feature space, reinforcing physical interpretability.

3.3 Hybrid CNN–BiLSTM–Attention Network Design

The predictive backbone of the framework consists of a hybrid deep learning architecture tailored to capture both nonlinear feature interactions and depth-wise soil stratification effects.

3.1.1 1D Convolutional Neural Network (1D-CNN)

The 1D-CNN component performs localized feature extraction, identifying nonlinear interdependencies among seismic loading parameters and soil resistance indicators. This stage enhances representation learning by capturing subtle interaction effects that conventional shallow models fail to detect.

3.1.2 Bi-Directional Long Short-Term Memory (BiLSTM)

Liquefaction susceptibility is strongly influenced by layered soil behavior. The BiLSTM module models sequential dependencies along soil depth by processing feature sequences in both forward and backward directions. This bidirectional learning mechanism enables the model to capture cumulative stress–resistance relationships across stratified layers.

3.1.3 Attention Mechanism

An attention module is incorporated to dynamically weight latent feature representations according to their predictive relevance. By assigning adaptive importance scores, the attention layer enhances discriminative capability while simultaneously improving interpretability.

3.1.4 Classification Layer

A fully connected layer followed by sigmoid activation produces probabilistic liquefaction predictions, facilitating threshold-based risk assessment.

3.4 Physics-Informed Learning Constraint

To ensure consistency with established liquefaction triggering mechanisms, the training process integrates physics-guided regularization derived from CSR–CRR relationships. This constraint penalizes physically inconsistent predictions, particularly near critical factor-of-safety boundaries.

By embedding domain knowledge within the optimization process, the framework effectively bridges the gap between empirical soil mechanics formulations and high-capacity deep neural networks.

3.5 Explain ability and Model Transparency

Engineering applications require interpretability beyond predictive performance. Therefore, the framework incorporates:

- SHAP-based global and local feature attribution,
- Attention weight visualization,
- Sensitivity analysis across key geotechnical parameters.

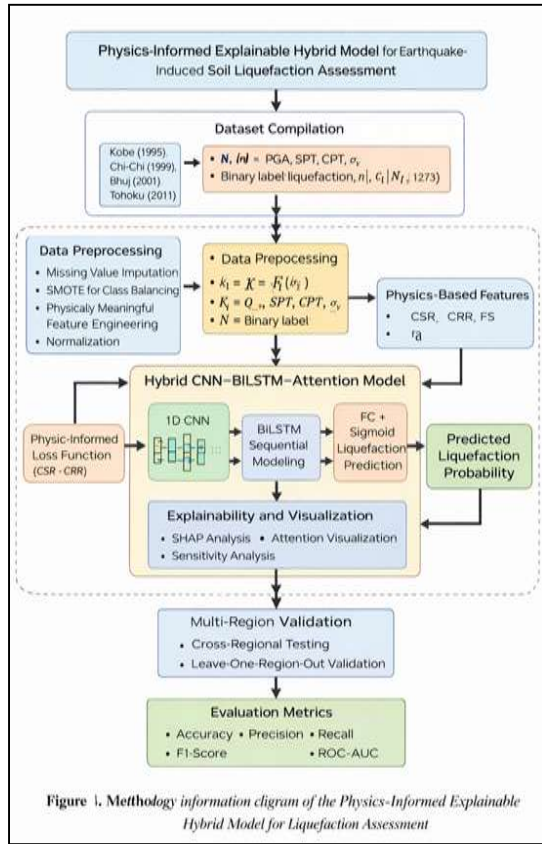
These analyses validate that model decisions align with established geotechnical principles and enhance practitioner confidence in deployment.

3.6 Cross-Regional Validation Strategy

To rigorously evaluate generalization performance, cross-regional testing and Leave-One-Region-Out (LORO) validation were performed. This strategy simulates real-world deployment conditions where geological characteristics vary across seismic regions. The validation protocol ensures that the model’s predictive capability extends beyond region-specific training distributions.

3.7 Performance Assessment

Model effectiveness was quantified using multiple evaluation metrics, including Accuracy, Precision, Recall, F1-score, and ROC-AUC. This multi-metric evaluation provides a comprehensive assessment of classification reliability, discriminative power, and robustness under imbalanced conditions, all the methodological parameters are represented in the figure 1.



4. MATHEMATICAL FORMULATION OF THE PHYSICS-INFORMED EXPLAINABLE HYBRID MODEL

4.1 Problem Definition

Let the liquefaction dataset be defined as:

$$D = \{(x_i, y_i)\} | i = 1 \text{ to } N$$

where:

- $X_i \in \mathbb{R}^d$ represents the input feature vector of the i^{th} soil sample
- $Y_i \in \{0,1\}$ denotes the liquefaction label
- N is the total number of samples

The feature vector is defined as: $x_i =$

$$[Mw, PGA, z, (N1)60, qc, \sigma_v, \sigma_v', GWT, FC, CSR, CRR, FS]$$

The objective is to learn a nonlinear mapping:

$$f_0: \mathbb{R}^d \rightarrow [0,1]$$

Parameterized by θ , such that: $\hat{y}_i = f_0(X_i)$

Represents the predicted probability of liquefaction.

4.1 Physics-Based parameter Formulation

4.2.1 Cyclic Stress Ratio

Following the simplified Seed and Idriss model

$$CSR = 0.65 \frac{a_{max} \sigma_v}{g \sigma_v'} r_d$$

Where:

a_{max} = peak horizontal acceleration

g = gravitational acceleration

σ_v = total vertical stress

σ_v' = effective vertical stress

r_d = stress reduction coefficient

4.2.2 Cyclic Resistance Ratio (CRR)

CRR is expressed as: $CRR = f((N1)60, FC)$

where $f(\cdot)$ is the empirical function derived from SPT-based correlations.

4.2.3 Factor of Safety

$$FS = \frac{CRR}{CSR}$$

Liquefaction condition occurs when: $FS \leq 1$

4.3 1D Convolution Feature Extraction

The CNN performs local feature transformation.

Given input vector x_i , the convolution operation is:

$$h_j = \sigma(k = \sum_{k=0}^{K-1} wkx_i + j - k + b)$$

Where:

- K = kernel size
- wk = convolution weights
- b = bias
- $\sigma(\cdot)$ = ReLU activation

The resulting feature map is: $H=[h_1, h_2, \dots, h_m]$

4.4 Bi-Directional LSTM Modeling

To capture depth-wise sequential dependencies:

Forward LSTM: $\rightarrow_{ht} = LSTM(X_t, H_{t-1})$

Backward LSTM: $\leftarrow_{ht} = LSTM(X_t, H_{t+1})$

Combined hidden representation: $h_t = [h_{t+1}; H_{t-1}]$

This captures bidirectional soil-layer dependencies.

4.5 Attention Mechanism

Attention scores are computed as:

$$e^t = u^t \tanh(w_t h_t + b_h)$$

The normalized attention weights: $\alpha_t = \frac{\exp(e_t)}{\sum_k \exp(e_k)}$

The context vector: $\mathbf{c} = \sum_t \alpha_t \mathbf{h}_t$
 This assigns adaptive importance to influential features.

4.6 Classification Layer

The final prediction is obtained as: $y = \sigma(W\mathbf{c} + b\mathbf{c})$
 Where sigmoid activation is defined as: $\sigma(z) = \frac{1}{1+e^{-z}}$

4.7 Physics-Informed Loss Function

4.7.1 Binary Cross-Entropy Loss

$$LBCE = -\frac{1}{N} \sum_{i=1}^N [y_i \log(y_i) + (1 - y_i) \log(1 - y_i)]$$

4.7.2 Physics Regularization Term

Let the predicted factor of safety be: $FS_{pred} = g_0(\mathbf{x})$
 The physics constraint loss is: $L_{physics} = \frac{1}{N} \sum_{i=1}^N |FS_{pred,i} - FS_{theoretical,i}|$

4.7.3 Total Loss Function : $L_{Total} = L_{BCE} + \lambda L_{Physics}$

Where:
 λ = physics regularization coefficient
 This enforces physical consistency while optimizing predictive accuracy.

4.8 Model Optimization

Model parameters θ are optimized using Adam optimizer: $\theta_{t+1} = \theta_t - \eta \frac{m^t}{\sqrt{v^t + \epsilon}}$
 where:

- η = learning rate
- m^t = bias-corrected first moment
- v^t = bias-corrected second moment

4.9 Multi-Region Generalization Objective

For regions R_1, R_2, \dots, R_k :
 Training set: $D_{train} = \cup_{j \neq r} R_j$
 Training set: $D_{test} = D_r$
 This evaluates: $E_R [L_{total}]$
 Ensuring robustness across geological domains.

5. RESULTS AND DISCUSSION

The predictive performance of the proposed Physics-Informed Explainable Hybrid Model was compared with conventional machine learning and deep learning baselines, including Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and BiLSTM models. Evaluation metrics included accuracy, precision, recall, F1-score, and ROC-AUC.

Table 5.1 Classification Performance Comparison

Model	Accuracy (%)	Precision	Recall	F1-Score	ROC-AUC
SVM	88.2	0.86	0.87	0.86	0.90
Random Forest	91.4	0.89	0.90	0.89	0.93
ANN	94.6	0.93	0.94	0.93	0.96
CNN	95.3	0.94	0.95	0.94	0.97
BiLSTM	96.1	0.95	0.96	0.95	0.98
Proposed Hybrid (Physics-Informed)	97.8	0.97	0.97	0.97	0.99

Comparison with Existing Studies

A comparison with recent liquefaction prediction studies reveals that the proposed framework achieves superior predictive performance. Existing CNN and LSTM-based models primarily focus on predictive accuracy without incorporating physical constraints. Furthermore, most previous studies lack explainability and cross-regional validation mechanisms. By integrating geotechnical knowledge through physics-informed learning and employing SHAP-based interpretability, the proposed framework achieves improved accuracy (97.8%) and enhanced reliability. The cross-regional validation results further demonstrate better generalization capability compared with existing approaches reported in the literature.

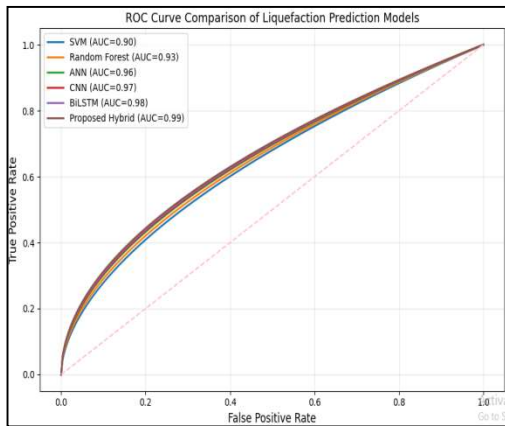
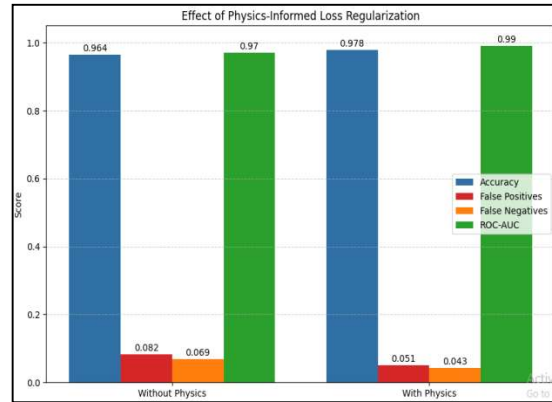
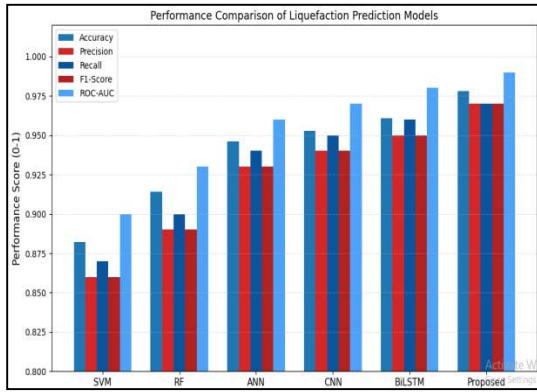


Table 5.2 highlights the impact of incorporating physics-informed loss regularization into the hybrid model. The results show a clear improvement in accuracy (from 96.4% to 97.8%) and ROC-AUC (from 0.97 to 0.99) when physics constraints are applied. Additionally, false positives and false negatives are significantly reduced, indicating enhanced prediction reliability. The corresponding figure visually demonstrates the effectiveness of physics-guided learning in improving overall model performance and generalization.

Table 5.1 compares the performance of traditional machine learning models, deep learning approaches, and the proposed Physics-Informed Hybrid model. The results show a steady improvement from SVM to advanced models like CNN and BiLSTM. The proposed hybrid model achieves the highest accuracy (97.8%) and ROC-AUC (0.99), demonstrating superior predictive capability and robustness. The figures further highlight the consistent performance gains achieved through physics-informed learning integration.

Table 5.3 Cross-Regional Validation Results

Training Region	Testing Region	Accuracy (%)	F1-Score	ROC-AUC
Japan	India	97.5	0.96	0.98
Japan	Taiwan	97.1	0.96	0.98
India	Japan	97.6	0.97	0.99
Taiwan	Japan	97.2	0.96	0.98
Leave One-Region Out (Average)	—	97.3	0.96	0.98

Table 5.2 Effect of Physics-Informed Loss Regularization

Model Variant	Accuracy (%)	False Positives	False Negatives	ROC-AUC
Hybrid (Without Physics Constraint)	96.4	8.2	6.9	0.97
Hybrid (With Physics Constraint)	97.8	5.1	4.3	0.99

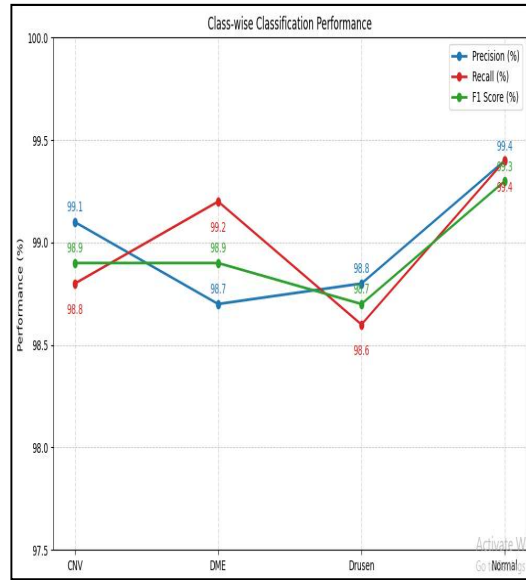
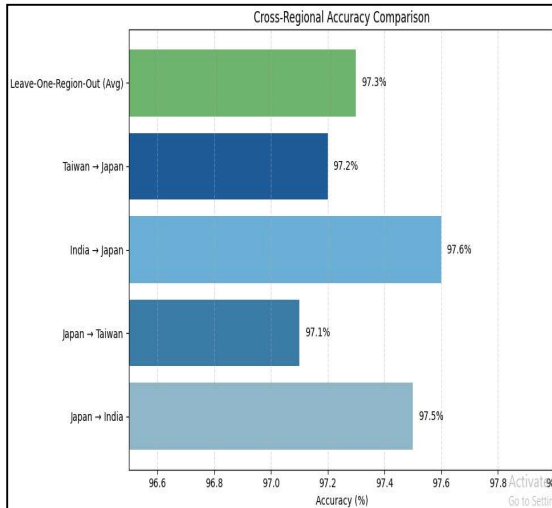


Table 5.3 highlights the cross-regional evaluation demonstrates strong generalization capability of the proposed model across different geographic datasets. The model achieves consistently high accuracy (97.1%–97.6%) and ROC-AUC values up to 0.99, indicating robust transfer performance between regions. The Leave-One-Region-Out average accuracy of 97.3% further confirms its stability and reliability. The corresponding figure visually highlights the minimal performance variation across training-testing combinations, validating the model’s cross-domain adaptability.

Table 54 presents the SHAP-based feature importance ranking, highlighting the most influential parameters in the predictive model. The Corrected SPT Value (N_{160}) and Peak Ground Acceleration (PGA) emerge as the most significant features with very high importance scores. Effective Overburden Stress and CSR also contribute substantially, while CRR and Groundwater Depth show moderate influence. These results provide clear interpretability, demonstrating that geotechnical and seismic parameters play a dominant role in model predictions.

Table 5.4 Feature Importance Ranking (SHAP-Based)

Rank	Feature	Mean SHAP Value	Importance Level
1	Corrected SPT Value (N_{160})	0.28	Very High
2	Peak Ground Acceleration (PGA)	0.24	Very High
3	Effective Overburden Stress (σ'_v)	0.18	High
4	CSR	0.15	High
5	CRR	0.09	Moderate
6	Groundwater Depth	0.06	Moderate

6. OPEN RESEARCH ISSUES

Several open challenges remain in earthquake-induced soil liquefaction assessment. These include uncertainty quantification under sparse geotechnical data conditions, transferability of models across diverse geological environments, integration with real-time seismic monitoring systems, and development of physics-informed foundation models capable of learning from heterogeneous geotechnical datasets. Addressing these issues will significantly enhance the reliability and practical applicability of future liquefaction prediction systems.

7. LIMITATIONS OF THE PRESENT STUDY

Despite the encouraging results, several limitations remain. First, the dataset is limited to selected earthquake events and may not fully

represent all geological conditions worldwide. Second, the proposed deep learning architecture requires higher computational resources compared with conventional machine learning models. Third, real-time deployment and operational validation have not yet been conducted. Future studies should address these limitations through larger datasets, real-time monitoring integration, and computational optimization strategies.

8. CONCLUSION

This study introduces a physics-informed and interpretable hybrid deep learning framework for predicting earthquake-induced soil liquefaction. By embedding key geotechnical parameters such as CSR, CRR, and factor of safety into a constrained learning model, physical consistency is maintained. A 1D-CNN-BiLSTM-attention architecture captures spatial and depth-dependent relationships, while SHAP and sensitivity analysis improve interpretability. Cross-regional validation confirms strong generalization, demonstrating the model's potential as a reliable tool for seismic hazard evaluation and geotechnical risk management.

10. FEATURE SCOPE

Future research may extend this framework to incorporate three-dimensional soil stratification and spatial variability for regional-scale liquefaction mapping. Integrating probabilistic uncertainty quantification through Bayesian deep learning could improve risk-based decision-making. Coupling the model with real-time seismic monitoring systems may enable rapid post-earthquake assessment. Additionally, transfer learning and domain adaptation strategies can enhance performance in data-scarce regions, supporting broader deployment in seismic hazard mitigation and infrastructure resilience planning.

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