ORIGINAL RESEARCH

A Deep Learning–Enhanced Framework for Predicting Liquefaction Susceptibility of Sandy Soils Using SPT-Based Geotechnical Data

Shima Aghakasiri [1], *, Ghodratollah Mohammadi [2], Amir Taban [3], Mohammad Emami Kourandeh [4]

[1] Department of Civil Engineering, S.T.C, Islamic Azad University, Tehran (Iran) ; sh.aghakasiri@iau.ir
[2] Department of Civil Engineering, S.T.C, Islamic Azad University, Tehran (Iran) ; Gh_mohammadi@azad.ac.ir
[3] Department of Civil Engineering, KH.A.C, Islamic Azad University, Khorramabad (Iran) ; am.taban@iau.ac.ir
[4] Department of Civil Engineering, S.T.C, Islamic Azad University, Tehran (Iran) ; M_emami@iau.ir
*Correspondence: sh.aghakasiri@iau.ir

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Abstract: Soil liquefaction remains one of the most critical challenges in geotechnical earthquake engineering, often resulting in severe ground deformation, settlement, and infrastructure failure during strong seismic events. Traditional empirical methods, while widely used, are limited in their ability to capture the nonlinear and complex interactions among soil parameters. This study introduces a hybrid deep learning framework based on a Convolutional Neural Network (CNN) optimized using the Multi-Verse Optimizer (MVO) to predict liquefaction potential and post-liquefaction settlement. A comprehensive geotechnical database consisting of 300 borehole records from the northern provinces of Iran—including SPT data, groundwater level, soil type, fine content, and liquefiable depth—was used for model training and evaluation. The hybrid CNN–MVO model demonstrated high predictive capability, achieving regression coefficients exceeding 90% and Mean Squared Error (MSE) values below 0.5 across training, testing, and validation sets. Sensitivity analysis revealed that fine content (FP) had the strongest influence on liquefaction potential, followed by SPT-N and soil type. The results confirm that combining CNN with MVO significantly enhances model accuracy and parameter interpretability, offering a robust alternative to traditional liquefaction assessment methods. The proposed model can support engineers in developing more reliable seismic risk evaluations and mitigation strategies in liquefaction-prone regions.

Keywords: Liquefaction, Deep Learning, CNN–MVO, SPT, Geotechnical Engineering, Soft Computing.

List of abbreviations:

MVO - Multiverse Optimization Algorithm

CNN - Convolutional Neural Networks

SPT -Standard Potential Test

CSR -Cyclic Stress Ratio

CRR -Cyclic Resistance Ratio

σ -total vertical stress

σv -the effective vertical stress

r_d - the stress reduction factor

a_{max} -represents the maximum horizontal acceleration due to the earthquake at the ground surface

g -the acceleration due to gravity

Z - Depth (m)

Highlights:

- A redesigned and optimized hybrid deep learning framework (CNN–MVO) is introduced to evaluate liquefaction susceptibility using SPT data.
- Five key geotechnical parameters (soil type, groundwater depth, fine content, SPT-N, depth of liquefiable layer) are used as model inputs.
- A curated dataset of over 300 boreholes from northern Iran is used for training and validation.
- The proposed CNN–MVO architecture achieves high prediction accuracy (R > 0.90 and MSE < 0.5).
- Sensitivity analysis identifies fine content as the most influential factor controlling liquefaction behavior.
- The framework offers a robust, efficient, and data-driven tool to support seismic geotechnical risk assessment.

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1. Introduction

Soil liquefaction is a major seismic hazard that has repeatedly caused severe geotechnical failures during major earthquakes such as Niigata (1964) and Christchurch (2011). Evaluating liquefaction susceptibility is therefore critical for seismic design, hazard mitigation, and risk assessment. Traditional empirical approaches such as SPT-based CSR–CRR procedures remain the most widely used methods in practice; however, these approaches are limited by simplifying assumptions regarding soil behavior, seismic demand, and spatial variability [1-3]. Understanding the dynamic behavior of soil under earthquake loading is a fundamental component of seismic hazard assessment. As highlighted in recent studies on structure soil structure interaction, the response of geotechnical systems plays a critical role in the overall seismic performance of infrastructures, emphasizing the necessity of accurate soil behavior modeling during strong ground motions [4]. These findings further reinforce the importance of evaluating soil failure mechanisms particularly liquefaction, which remains one of the most destructive geotechnical hazards associated with earthquakes. Moreover, nonlinear seismic analyses on ground–structure systems have demonstrated that variations in soil properties can significantly influence stress distribution, deformation patterns, and the performance of underground structures, underscoring the crucial need for reliable predictive tools capable of capturing complex soil behavior [5]. Such insights provide strong motivation for employing advanced modeling techniques to assess the susceptibility of sandy soils to liquefaction under cyclic loading. In broader seismic engineering contexts, recent investigations into the performance of seismic energy absorption systems also highlight the critical role of soil conditions in controlling ground motion effects transmitted to structures [6]. While these studies primarily focus on structural engineering, they collectively point toward a consistent conclusion: the behavior of soil during earthquakes must be accurately assessed to mitigate seismic risks effectively. Building upon this body of knowledge, the present study integrates geotechnical data with advanced artificial intelligence techniques to develop a robust predictive model for liquefaction potential. The hybrid CNN–MVO framework proposed here seeks to overcome the limitations of traditional empirical correlations by capturing the nonlinear, multivariate dependencies among key soil parameters such as SPT values, fine content, groundwater level, and liquefiable layer depth.

With rapid progress in artificial intelligence, machine learning (ML) and deep learning (DL) techniques have shown strong potential to model nonlinear soil behavior under cyclic loading. Recent studies have demonstrated that ML algorithms can significantly improve the accuracy of liquefaction prediction compared with empirical correlations. For example, Kumar et al. (2023) employed machine learning using SPT parameters to predict liquefaction susceptibility and reported superior performance relative to conventional methods [7]. Deep neural networks have also been successfully used to model liquefaction behavior based on shear-wave velocity profiles, highlighting their capability to capture complex soil responses under dynamic loading [8].

Advanced probabilistic and data-driven frameworks have further extended liquefaction assessment, including Bayesian belief networks for estimating lateral displacements caused by liquefaction [9], fragility-based liquefaction ground failure models [10], and large-scale data analytics for liquefaction consequence evaluation [11]. Other researchers have investigated hybrid models, such as GA–SVM and GWO–SVM combinations, which have shown improved predictive performance for liquefaction triggering using multi-regional datasets [12, 13].

More recent studies have focused on modeling pore-pressure generation and cyclic response using ML and deep learning. Choi & Kumar

(2023) demonstrated the usefulness of ML models for predicting pore-pressure response in liquefiable sands subjected to cyclic loading [14]. Several investigations have also explored advanced frameworks for liquefaction assessment, including state parameter-based ML evaluation [15], multilayer fast liquefaction disaster assessment systems [16], and comprehensive reviews summarizing ML-based liquefaction prediction techniques from 1994 to 2021 [17]. Moreover, deep learning methods such as CNNs and LSTMs have been applied to seismic site response modeling in downhole array stations, indicating the strong adaptability of DL techniques in geotechnical dynamics [18].

Despite these advances, CNN-based hybrid optimization models tailored specifically for SPT-driven liquefaction prediction remain limited. Most existing studies have focused on either conventional ML models or deep networks without systematic optimization. Therefore, there is still a need for developing improved hybrid deep learning frameworks that integrate deep feature extraction and global optimization to enhance the predictive performance and interpretability of liquefaction assessment models. Motivated by these gaps, the present study introduces an optimized CNN–MVO hybrid model trained on a large SPT-based geotechnical database from northern Iran to improve the reliability of liquefaction susceptibility prediction.

This study contributes a restructured and optimized CNN–MVO hybrid model for liquefaction prediction using SPT-based data. The model is trained using a region-specific dataset from northern Iran, enabling improved adaptability and interpretability. The main innovations of the study include:

- Development of a refined deep learning architecture integrating CNN and MVO for liquefaction susceptibility assessment.
- Use of a large, unified field database from boreholes in northern Iran.
- Comprehensive sensitivity analysis to identify dominant geotechnical parameters influencing liquefaction behavior.
- A practical data-driven assessment framework suitable for seismic hazard evaluation and engineering decision-making.

2. Theoretical Foundations of the Study

The evaluation of liquefaction resistance has long been grounded in empirical approaches built upon extensive in-situ testing and post-earthquake observations. Field methods such as the Standard Penetration Test (SPT), Cone Penetration Test (CPT), and shear wave velocity profiling continue to serve as the primary tools for assessing liquefaction hazard, given their practicality and decades of validation in geotechnical engineering practice [19, 20]. These methods have played a central role in characterizing subsurface conditions and have provided essential correlations for estimating the cyclic stress ratio (CSR) and cyclic resistance ratio (CRR) in engineering evaluations.

Documented evidence from major seismic events highlights the destructive consequences of liquefaction, including lateral spreading, sand ejecta, ground settlement, and foundation failures. For instance, the 2011 Great East Japan Earthquake triggered widespread liquefaction across both coastal and inland regions extending nearly 500 km from the epicentral area resulting

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in severe deformation and extensive infrastructure disruption [21]. Similar liquefaction-related damage has been reported in the Maule (2012), Tōhoku (2011), and Christchurch (2011) earthquakes, underscoring the need for reliable predictive tools [3]. Traditional metrics such as the Liquefaction Potential Index (LPI), typically derived from SPT and CPT inputs [22, 23], have been widely used to produce liquefaction susceptibility maps, such as those developed by Maurer et al. (2014) for regions in Turkey[24]. Complementing these deterministic tools, probabilistic approaches including Newmark-type displacement analyses [25]. underscore the importance of integrating soil stratigraphy, dynamic behavior, and ground motion characteristics. The fundamental mechanism of liquefaction is generally illustrated in Figure 1.

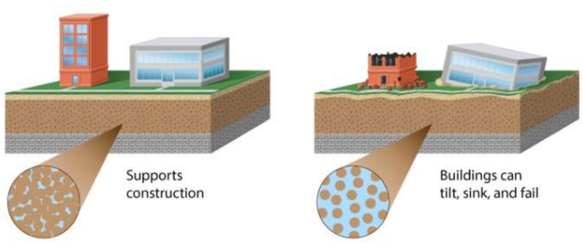

Figure 1. Liquefaction Mechanism – Soil particles become buoyant due to increased pore water pressure.

In recent years, the rapid advancement of artificial intelligence has significantly transformed liquefaction research, creating new pathways for modeling complex, nonlinear soil behavior. Deep learning, in particular, has expanded predictive capabilities. Zhang et al. (2023) trained a Convolutional Neural Network (CNN) on more than one million nonlinear site-response simulations to detect the onset and timing of liquefaction, demonstrating the remarkable scalability of DL models[26]. Similarly, Şehmusoğlu et al. (2025) conducted an extensive comparative study involving CNNs, LSTMs, BiLSTMs, and other ML/DL architectures for liquefaction prediction, highlighting the strengths and limitations of each model[27]. Bai et al. (2024) introduced a CNN–GA hybrid framework to examine correlations between SPT and CPT data for liquefaction classification[28], whereas Ghani et al. (2025) applied multiple advanced algorithms CNN, LSTM, CatBoost, and XGBoost to classify soils and estimate liquefaction potential[29, 30]. Chou and Pham (2024) further contributed to this domain by developing a JS–CNN–XGB hybrid architecture that combined global optimization with both deep and gradient-boosting models[31]. Additionally, Kumar et al. (2023) employed DNNs, CNNs, and Simple RNN models to estimate the probability of liquefaction occurrence based on multiple influencing parameters[7, 32]. Shafiei et al. (2022) expanded this research direction by proposing an ELM–MVO hybrid model for forecasting liquefaction effects in seismic tunnel linings embedded within sandy layers[33].

Beyond deep learning applications, empirical and experimental studies still provide critical insight. Chen et al. (2016) evaluated several empirical liquefaction prediction methods across different soil depths using extensive earthquake datasets from Taiwan[34]. Dynamic analyses by Hadi Shahir et al. (2012) emphasized the pivotal role of soil permeability in pore pressure generation and dissipation during seismic loading, supported by centrifuge test results[35]. These findings highlight that soil behavior during liquefaction is governed by both mechanical characteristics and hydrodynamic interactions.

Soft computing methods such as fuzzy logic, gene expression programming, and hybrid optimization have also become prominent in recent years. For example, Samui and Hariharan (2015) introduced the Minimax Probability Machine for

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CPT-based liquefaction classification[36], while Muduli and Das (2015) incorporated multi-gene genetic programming with SPT data to account for uncertainty in seismic liquefaction prediction[37]. Javadi et al. (2009) developed an intelligent finite element framework by embedding neural networks into stress–strain simulations under dynamic loading[38]. These studies collectively demonstrate a growing reliance on soft computing, hybrid frameworks, and data-driven modeling in liquefaction assessment.

Overall, the convergence of empirical knowledge, laboratory investigations, soft computing, and deep learning techniques has created a more holistic foundation for understanding and predicting liquefaction behavior. While empirical models remain essential, AI-driven frameworks offer the ability to capture complex interactions between soil parameters, seismic loading, and subsurface conditions that traditional approaches may overlook. Motivated by these advancements, the present research introduces a hybrid CNN–MVO model specifically developed for liquefaction assessment in the Mazandaran coastal region, aiming to enhance predictive performance and provide a robust, data-driven tool for regional geotechnical hazard mitigation.

3. Research Methodology

The research methodology adopted in this study was structured to address both the primary and secondary research objectives while seeking to identify a robust and generalizable predictive model applicable to sandy soils susceptible to liquefaction under similar geotechnical conditions. The methodological framework consists of a sequence of systematic and, in some cases, parallel steps designed to ensure scientific rigor, data reliability, and optimal model performance. The main stages of the methodology are summarized below:

1. Comprehensive investigation of liquefaction hazards and review of existing analytical and predictive methods.
2. Assessment of liquefaction potential in geotechnical projects located across the northern provinces of Iran, with emphasis on areas known to contain saturated sandy or silty layers.
3. Compilation of all necessary geotechnical data required for training artificial neural networks and deep learning models.
4. Data preprocessing, including statistical screening, quality control, and removal of outliers to ensure a consistent and reliable database.
5. Identification and selection of appropriate input and output variables aligned with liquefaction mechanisms and consistent with deep learning requirements.
6. Development and coding of the proposed hybrid deep learning model, integrating a Convolutional Neural Network (CNN) with the Multi-Verse Optimizer (MVO) algorithm for enhanced parameter optimization.
7. Implementation and training of the CNN–MVO model using the compiled geotechnical dataset.
8. Performance evaluation of the developed model using statistical assessment tools and prediction accuracy metrics to validate the model's reliability and generalizability.

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3.1.Liquefaction Hazard Calculation

Ground failure is one of the principal sources of damage during earthquakes. Such failure may arise from ground cracking, differential settlements, lateral displacements, or the sudden loss of soil shear strength. In saturated, loose to medium-dense sandy soils, the buildup of excess pore water pressure during cyclic seismic loading can reduce effective stress to near-zero values, triggering a phenomenon known as soil liquefaction. When shear strength is lost, the affected soil behaves temporarily like a viscous fluid, often manifesting in the field as sand boils, lateral spreading, and flow-type deformations.

Considering the presence of thick saturated sandy and silty layers at varying depths in the study region and supported by available SPT data the evaluation of liquefaction potential was carried out using established engineering procedures.

Among the various available liquefaction assessment methods, the Seed et al. (1983) simplified procedure remains one of the most widely used and validated approaches[39]. This method estimates liquefaction potential based on Standard Penetration Test (SPT) results and evaluates the cyclic demand imposed by earthquake loading on soil layers.

In this framework, the Cyclic Stress Ratio (CSR) representing the seismic shear stress induced in a soil layer is calculated either through detailed seismic site-response analyses or using the simplified formulation proposed by Seed et al. (1983)[39]. The commonly adopted equation is:

$$\mathrm{CSR}=(\sigma_{av}/\sigma_0') = 0.65\left(\frac{a_{max}}{g}\right)\left(\frac{\sigma_v}{\sigma_v'}\right)r_d \quad (1)$$

At the ground surface, $r_d = 1$, and its value decreases progressively with depth as seismic stresses attenuate within the soil profile. The variation of r_d with depth, derived from empirical and analytical studies, is illustrated in Figure 2.

This calculated CSR is subsequently compared with the Cyclic Resistance Ratio (CRR) to evaluate the likelihood of liquefaction triggering under the design earthquake scenario.

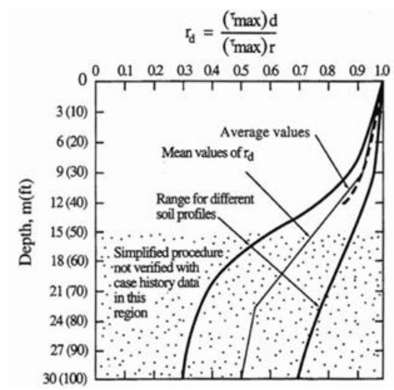

Figure 2. Stress reduction coefficient based on the method Seed et al., (1983)[39]

The cyclic shear strength of soil defined as the level of cyclic shear stress required to generate excess pore water pressure sufficient to reduce effective stress to zero can be estimated through in-situ tests such as the Standard Penetration Test (SPT). Numerous empirical correlations have been developed to compute the Cyclic Resistance Ratio (CRR) based on corrected SPT blow counts, fines content, and in some cases, soil plasticity parameters. One of the most widely referenced correlations is the chart introduced by Seed et al. (1983)[39], presented in Figure 3, which provides CRR (τ_{av} / σ'_0) values as a function of normalized SPT data.

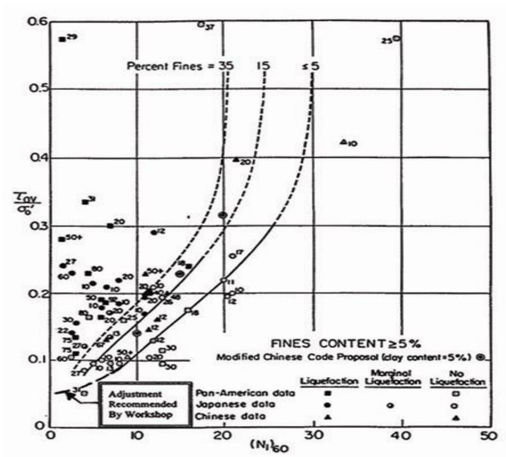

Figure 3. **Chart for calculating the Cyclic Resistance Ratio (CRR) based on SPT values [39]**

The factor of safety against liquefaction is defined as the ratio of the soil's cyclic shear resistance to the imposed cyclic shear stress. A factor of safety less than one indicates that the soil is expected to undergo liquefaction during the design seismic event. In this study, liquefaction analyses were performed using the Seed et al. (1983)[39] simplified procedure, implemented through LiquefyPro software (version 4.5D, CivilTech). Boreholes exhibiting stratigraphic and geotechnical characteristics conducive to liquefaction were selected for detailed evaluation.

The analyses were conducted using earthquake parameters representative of the seismicity of the northern provinces, specifically a peak ground acceleration of a_{max}=0.3g and a moment magnitude of M = 7. Figure 4 illustrates an example of the computations and simulation outputs produced by LiquefyPro.

To strengthen the geotechnical database of this study, the above calculations and modeling procedures were applied to more than 300 boreholes obtained from geotechnical investigation projects across the northern regions of the country. These extensive analyses provided a rich dataset for subsequent deep learning model development and validation.

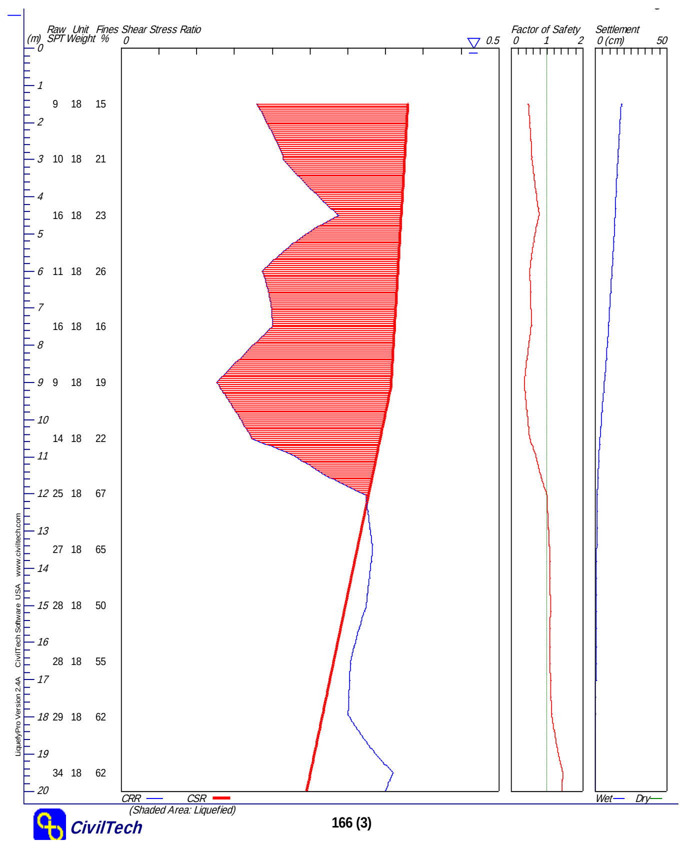

Figure 4. A sample of LiqufyPro software results in predicting liquefaction potential

3.2. *Convolutional Neural Networks (CNN)*

Convolutional Neural Networks (CNNs) represent a specialized class of artificial neural networks that have gained significant attention in recent decades due to their powerful capability in feature extraction and pattern recognition. Unlike conventional neural networks, which rely primarily on matrix multiplication, CNNs incorporate a mathematical operation known as convolution within at least one of their layers [32].

A typical CNN architecture consists of an input layer, several hidden layers, and an output layer. In feedforward neural networks, hidden layers process information through activation functions, transforming intermediate representations before passing them to subsequent layers. In CNNs, however, hidden layers include distinctive components such as convolutional layers, pooling layers, and fully connected layers, each performing specific mathematical and feature-extraction operations.

The core operation involves applying convolutional kernels (filters) over the input data to capture local spatial patterns. These kernels slide across the input matrix and compute dot products, generating feature maps that detect meaningful characteristics such as edges, textures, or structural variations. One of the main advantages of CNNs over traditional machine learning methods is their ability to automatically learn filter weights from the training data, eliminating the need for manual feature engineering.

The architecture of CNNs is inspired by the biological structure of the visual cortex in the human brain. Each artificial neuron responds to stimuli within a limited spatial region known as the receptive field. Multiple receptive fields overlap to collectively perceive the entire input space, enabling the network to identify both local and global patterns. Owing to this hierarchical and biologically inspired design, CNNs require far less preprocessing compared to classical image-processing or signal-based feature extraction techniques, making them particularly effective for complex classification, regression, and pattern recognition tasks.

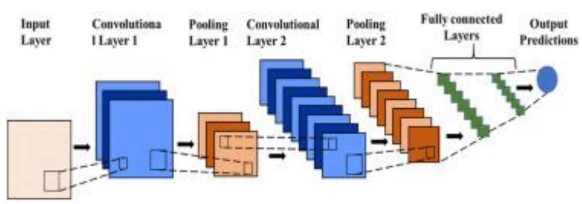

Figure 5. Convolutional Neural Network (CNN) and its operation (Kumar et al,. 2023)[32]

3.3. *Multiverse Optimization Algorithm (MVO)*

The Multi-Verse Optimization (MVO) algorithm is a population-based metaheuristic inspired by concepts from cosmology and multiverse theory. Like other evolutionary algorithms, MVO operates through two main mechanisms: exploration, which searches for global optima by examining diverse regions of the search space, and exploitation, which refines promising solutions to achieve higher accuracy.

In MVO, each candidate solution is treated as a separate universe, and the variables within a solution are regarded as objects located within that universe. To guide the optimization process, each universe is assigned an inflation rate, directly proportional to its fitness value. Universes with higher inflation rates are considered more favorable, influencing the movement and updating of other universes in the population. The conceptual framework of MVO draws from three primary cosmological phenomena (Mirjalili et al., 2016)[40]:

- White holes: Represent sources from which matter exits; used in the algorithm to allow high-quality solutions to contribute information to others, supporting exploration.
- Black holes: Act as sinks that absorb matter; used to remove poor-quality solutions and move them toward promising areas, enhancing global search capabilities.
- Wormholes: Provide shortcuts between universes; implemented to execute exploitation by allowing solutions to move randomly but intelligently toward better positions regardless of relative inflation rates.

Unlike traditional optimization algorithms that use iteration-based terminology, MVO employs the term time, aligning with the cosmological interpretation of multiverse dynamics. This unique combination of exploration and exploitation mechanisms makes MVO an effective optimizer for complex, high-dimensional search problems, including hyperparameter tuning in deep learning architectures such as the CNN–MVO framework used in this study.

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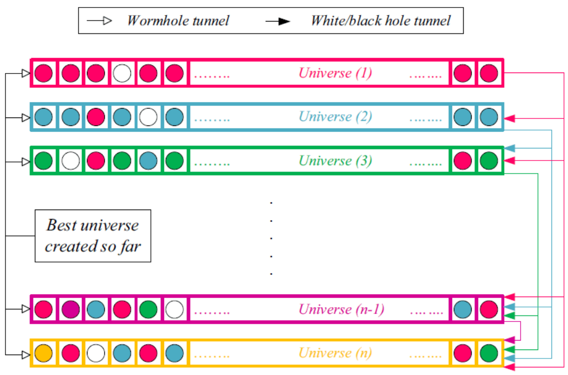

Figure 6. **Schematic representation of the MVO algorithm [40]**

3.4. *Geotechnical Studies*

The reliability and precision of computational and predictive methods are highly dependent on the quality and comprehensiveness of the underlying database. Both the volume and accuracy of input data significantly influence the performance of machine learning and deep learning models. In this study, an extensive geotechnical database was compiled using data obtained from site investigations conducted across the northern regions of Iran. A sample field log of the drilled boreholes from these projects is presented in Figure 7.

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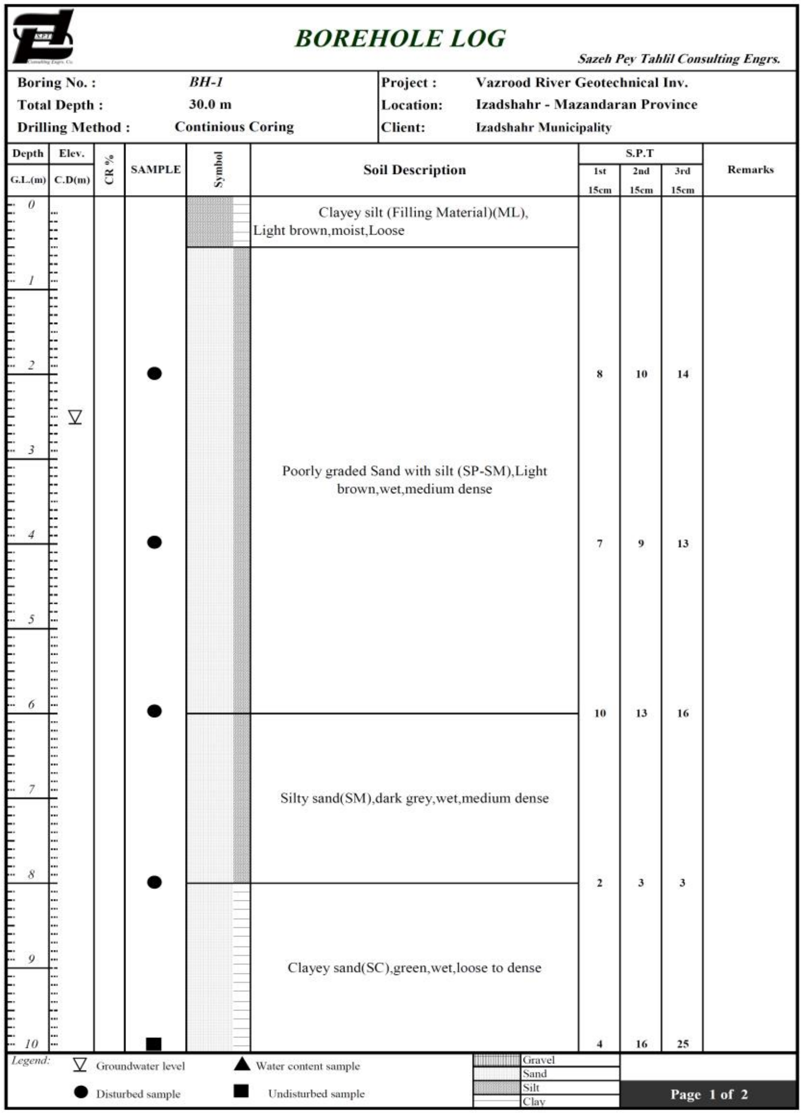

Figure 7. illustrates an example of field logs from drilled boreholes.

Geotechnical investigations were carried out by local engineering companies in major cities of Mazandaran and Gilan provinces, including Amol, Babol, Sari, Chalus, Astaneh Ashrafieh, Anzali, and Astara. During the drilling operations, Standard Penetration Tests (SPT) and shear wave velocity (Vs) measurements were performed to characterize subsurface soil properties. Following the drilling process, collected soil samples underwent comprehensive laboratory testing, including grain size distribution, hydrometer analysis, Atterberg limits, soil classification, moisture content determination, bulk density, specific gravity (Gs), direct shear tests, unconfined compression strength, triaxial compression tests, permeability measurements, and chemical analysis.

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Considering the parameters affecting liquefaction evaluation, the results of these geotechnical tests were examined in detail, and the most essential factors influencing liquefaction risk were identified. As outlined previously, the critical parameters include:

1. Soil type
2. Soil density
3. Groundwater level
4. Fine-grained soil content
5. Regional seismicity

Based on these key parameters, all geotechnical study reports were reviewed, and relevant data were extracted accordingly. Figure 8 illustrates a typical particle-size distribution curve for sandy soils from one of the examined projects, while Figure 9 shows the corresponding SPT profile recorded in the same borehole. Similar evaluations were performed for over 100 geotechnical investigation projects within the targeted study area, forming the foundation of the database used in the present research.

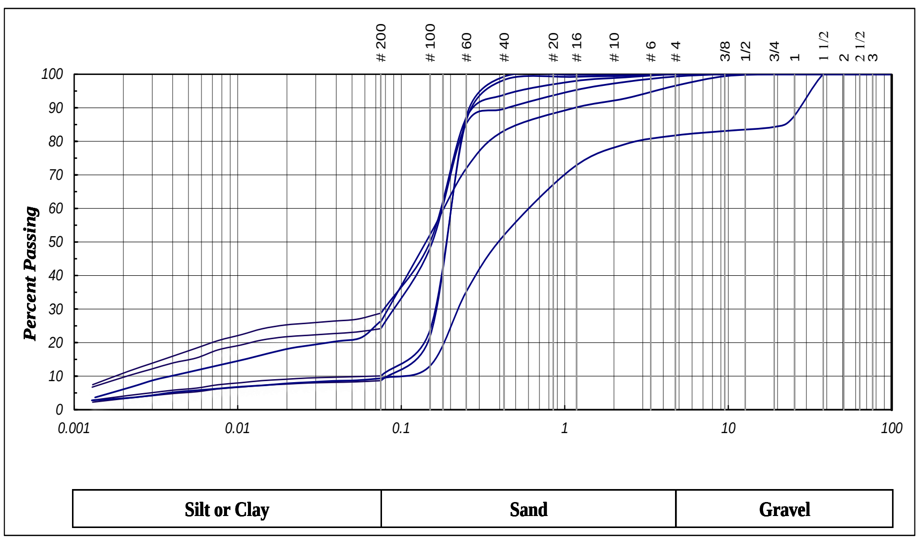

Figure 8. **Gradation curves of sandy soils from studied projects**

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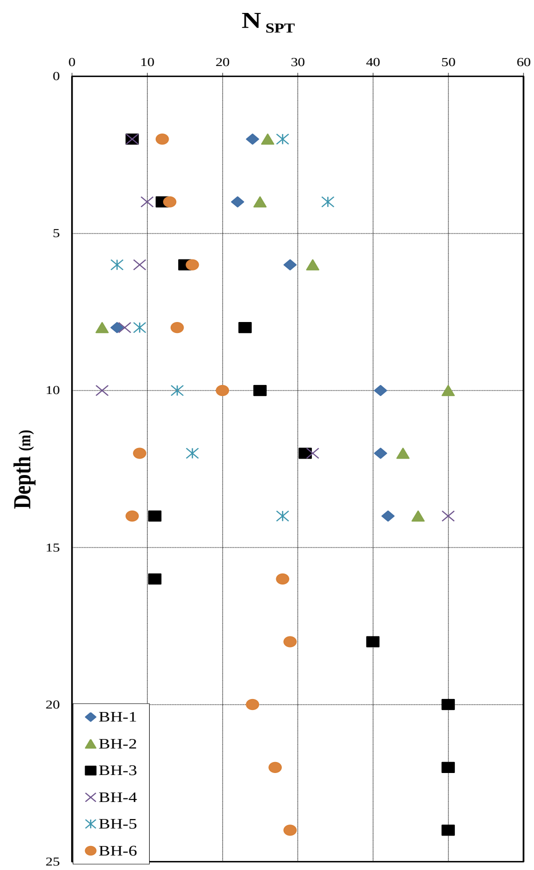

Figure 9. Results of SPT tests in one of the projects.

3.5. *Data Base*

To enrich the dataset and ensure the robustness of the proposed model, additional data were also incorporated from reputable scientific sources, including studies by Ansary & Ansary (2024)[41], Chithuloori & Kim (2025)[42], Ghani et al. (2025)[30], Gupta et al. (2022)[43], Hasan, Rahman & Fahim (2025)[44], Kumar, Muftuoglu & Dehghanian (2025)[45], and Pham (2021)[46].

The compiled database consists of approximately 300 samples, structured based on the most influential geotechnical and seismic parameters such as SPT blow counts, groundwater table depth, borehole depth, soil type, and other relevant characteristics.

For model development, the dataset was randomly divided into separate subsets to ensure unbiased learning:

1. Training dataset used for model learning and parameter adjustment.
2. Validation dataset used for monitoring and improving model generalization.

This random partitioning strategy helps prevent overfitting and enhances the predictive reliability of the deep learning model.

3.6. *Deep Learning Method*

The implementation of the deep learning framework was conducted following the preprocessing and thorough evaluation of the compiled geotechnical data. As emphasized in previous studies (Shafiei et al., 2022)[33], the performance of deep learning models is highly dependent on the size, accuracy, and representativeness of the input database.

Accordingly, the first step involved defining input and output parameters based on the most common and reliable geotechnical tests performed in engineering practice. Considering the availability of approximately 300 data points from geotechnical investigations and liquefaction analyses across the northern provinces, the parameters were selected to capture the essential physical and dynamic characteristics of the soil. The final set of input and output variables used for model training and prediction is presented in Table 1.

Subsequently, the proposed deep learning model utilizing a hybrid CNN–MVO architecture was developed and trained on the structured dataset. The integration of convolutional neural networks with the Multi-Verse Optimizer allowed for efficient extraction of nonlinear features and enhanced optimization of model hyperparameters, ultimately contributing to improved prediction accuracy.

Table 1. Sample Data from the Deep Learning Database

Output Parameter		Input Parameters				
SD (mm)	LP	SP	GWL (m)	FP (%)	Nspt	D (m)
41	1.20	5	8	18	6	5
18	1.11	3	5	13	7	4
21	1.23	5	3	25	5	8
12	1.08	5	10	26	9	10
11	1.03	4	2	21	12	6
26	1.25	6	2.5	18	11	7
23	1.13	6	4	15	16	4
13	0.98	7	3.6	17	25	11
16	0.95	4	3.2	15	33	12
14	0.98	2	6	16	20	5
31	1.12	4	4.6	10	25	6
10	0.88	3	2.8	8	35	7
33	1.20	6	3.2	11	11	4
32	1.21	5	3.5	18	10	5
26	1.13	8	4.1	20	16	8
15	1.05	10	7.5	23	20	10
18	1.06	9	5.3	5	23	16
11	0.92	12	6.3	8	33	10
16	1.01	11	2.6	6	15	8
13	1.03	10	3.7	9	18	6

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According to Table 1, the selected input parameters used for developing the predictive deep learning model include:

- Soil Type (SP): Classification of soil layers based on standard geotechnical criteria.
- Groundwater Level (GWL): Depth of the groundwater table at the project site.
- Fine Content (FP): Percentage of fine-grained particles passing the No. 200 sieve.
- Standard Penetration Test Value (Nspt): Corrected SPT blow counts representing soil resistance.
- Depth of Liquefiable Soil (D): The depth at which the soil layer exhibits susceptibility to liquefaction.

In addition to the input variables, two key output parameters chosen for their engineering relevance in liquefaction evaluations were defined:

- Liquefaction Potential (LP): The likelihood or probability of liquefaction occurrence under seismic loading.
- Estimated Settlement (SD): Anticipated post-liquefaction settlement of the ground surface.

After assembling the liquefaction-related dataset, all information was organized and preprocessed using Microsoft Excel. A series of preparation steps were applied to ensure compatibility with the deep learning framework. To enable the neural network to analyze categorical parameters such as soil type, encoding procedures were implemented. Soil classifications ranging from poorly graded sand (GP) to clayey sand (SC) were coded numerically from 1 to 12, allowing their incorporation into the model in a structured and machine-readable format.

3.7. *Deep Learning Method*

To evaluate the performance of the neural network models, quantitative metrics are necessary to measure how accurately the model predictions align with experimental or observed data. In this study, two primary evaluation indices were used: the Correlation Coefficient (R) and the Mean Squared Error (MSE).

Correlation Coefficient (R)

The correlation coefficient measures the strength of association between two variables, typically the predicted and experimental values. It is calculated using the following expression:

$$R = \frac{\sum(X-\bar{X})(Y-\bar{Y})}{\sqrt{\sum(X-\bar{X})^2(Y-\bar{Y})^2}} \quad (2)$$

where $\bar{x}$ and $\bar{y}$ represent the mean values of the two datasets. A higher R value indicates stronger correlation and better model performance. According to Rothman et al. (1987)[47], the correlation coefficient can be interpreted as follows:

Strong correlation:

$$|R| \geq 0.8 \quad (3)$$

Moderate correlation:

0

$.2 < |R| < 0.8$ (4)

Very weak correlation:

$|R| < 0.2$ (5)

In the present study, the R index was employed to evaluate the predictive performance of models developed using Multilayer Perceptron Neural Networks and deep learning techniques.

Mean Squared Error (MSE)

The Mean Squared Error quantifies the average of the squared differences between predicted and actual values. This metric places greater emphasis on larger errors and is commonly used to evaluate regression-based machine learning models. It is calculated as:

$$\text{MSE}=\frac{1}{N}\sum_{i=1}^{N}(E_i)^2 \quad (6)$$

where E_i denotes the prediction error for each data point. Lower MSE values indicate better model accuracy and improved predictive capability [48].

4. Research Methodology

The coding, training, and performance evaluation of the deep learning framework were carried out using MATLAB 9.5 (2018b). MATLAB is widely recognized among researchers for its extensive set of functions, flexible programming environment, diverse neural network architectures, and efficient training algorithms. Its strong computational capabilities and comprehensive statistical analysis tools make it highly suitable for solving complex engineering problems, including those encountered in geotechnical and earthquake engineering applications[49]. The MATLAB codes developed for this study are available; however, they are not included here in accordance with the publication requirements.

To assess the effectiveness of the proposed deep learning approach, two key performance indices were employed: the Regression Coefficient (R) and the Mean Squared Error (MSE). The training progression of the model is illustrated in Figure 10, which presents the learning curve during the training phase. Upon completion of training, the optimized network weights were stored, and the trained deep learning model became fully operational.

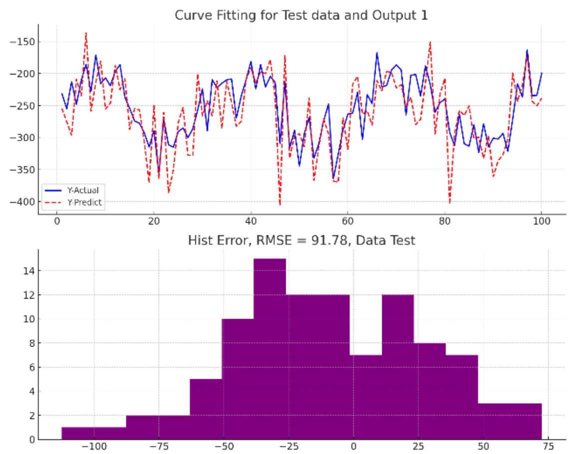

Figure 10. Training diagram for deep learning (Output 1)

Further evaluation is provided through the error histogram and the regression plots corresponding to the training, validation, and testing phases, as shown in Figures 11 and 12. These figures offer insight into error distribution patterns and the correlation between predicted and actual values across all data subsets.

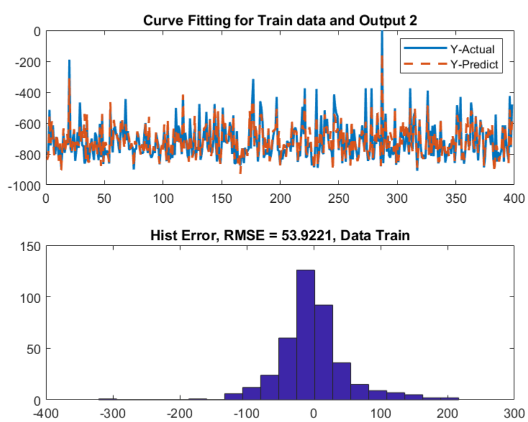

Figure 11. Training diagram for deep learning (Output 2)

Based on the visual evidence presented in Figures 10 through 13, the hybrid deep learning model exhibits strong predictive capability for both target outputs.

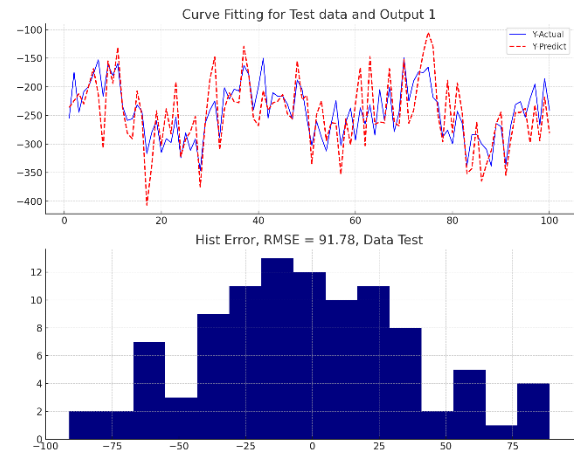

Figure 12. Testing diagram for deep learning (Output 1)

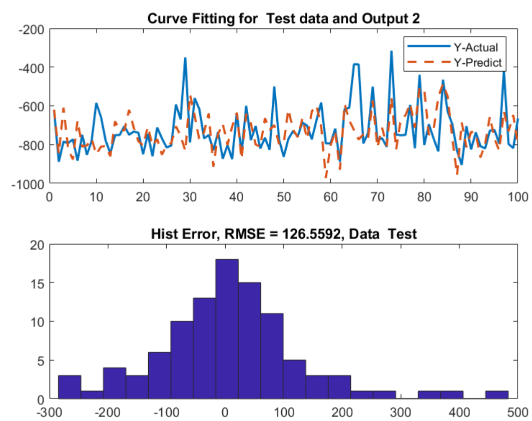

Figure 13. Testing diagram for deep learning (Output 2)

Moreover, Figures 14 and 15 indicate that the error indices for both outputs are less than 1, underscoring the high accuracy and reliability of the employed hybrid framework.

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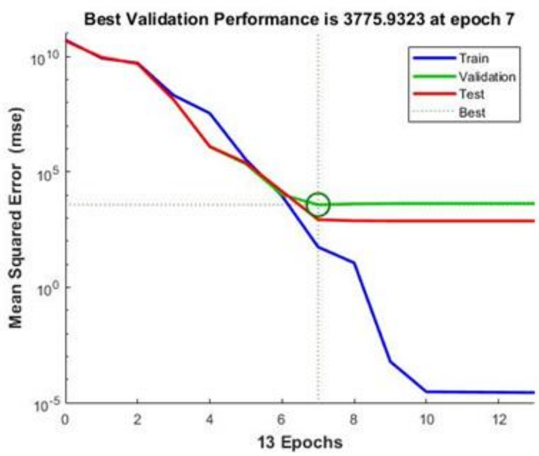

Figure 14. **Training curve of the deep learning hybrid code**

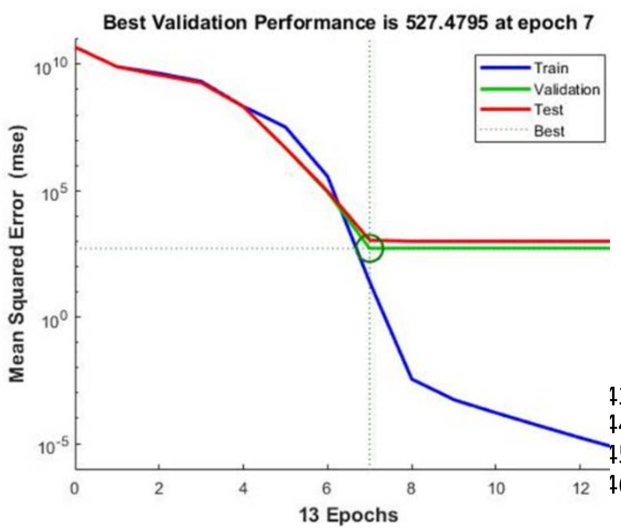

Figure 15. **Performance curve of the deep learning hybrid code**

The regression coefficient, commonly utilized in soft computing applications, serves as a primary measure for evaluating the strength of association between predicted and observed values. Figures 16 and 17 present the R-values obtained for the model. The results reveal coefficients exceeding 90%, confirming the robust performance, consistency, and acceptable predictive accuracy of the implemented hybrid CNN–MVO model based on established evaluation criteria.

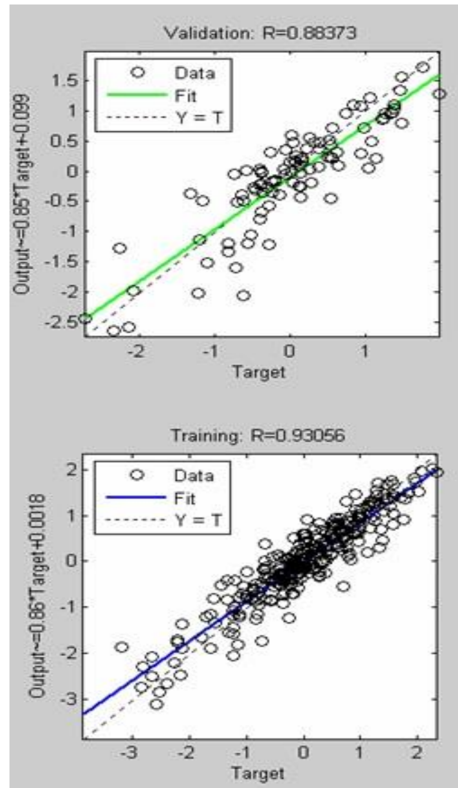

Figure 16. **Regression coefficient of the deep learning hybrid code (Output 2)**

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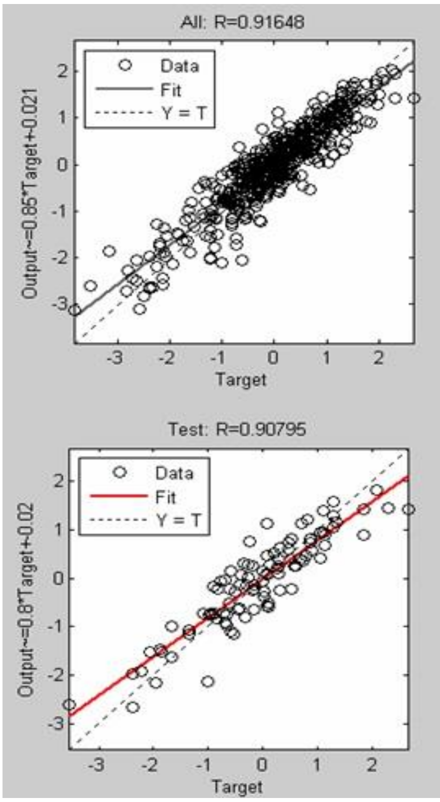

Figure 17. **Regression coefficient of the deep learning hybrid code (Output 1)**

5. Sensitivity Analysis

Machine learning and deep learning models typically demonstrate strong performance when trained on datasets that are both reliable and sufficiently large. However, despite their predictive effectiveness, these models are often criticized for their "black-box" nature, meaning that the internal relationships between input parameters and outputs are not always transparent. For this reason, sensitivity analysis plays a vital role in interpreting model behavior and understanding how variations in each input affect the prediction results.

Several approaches for conducting sensitivity analysis in neural networks have been introduced in the literature. Lou et al. examined these techniques and concluded that conventional methods cannot fully quantify the magnitude and direction of input effects across the entire input domain[50]. To address this limitation, they proposed a statistical method based on calculating the derivative of outputs with respect to inputs referred to as output sensitivity to input. Their findings, demonstrated through a case study on pipeline productivity, showed that analyzing internal relationships in neural networks enhances user confidence and supports broader application of such models in engineering and scientific analyses[49].

In the present study, the derivative-based sensitivity approach was applied to optimized network structures at each stage of evaluation. The sensitivity of model outputs relative to five primary input parameters namely soil type, fine content, liquefiable depth, SPT-N value, and groundwater level was investigated. To ensure representativeness, 500 sample points within the five-dimensional input space were generated using a normal distribution function. Given that the number of available data points (300 samples) was insufficient for derivative-based sensitivity estimation, the SIMLAB software was used to support the generation and analysis of additional data points.

For sensitivity quantification, the statistical relative sensitivity method proposed by Lou & Ruan (2001)[51] was adopted. This method computes five key percentiles D10, D25, D50, D75, and D90 from the distribution of relative sensitivity values. These percentiles provide a comprehensive understanding of the direction and magnitude of sensitivity trends across the input domain. The interpretation of these indices, based on Emami (2009)[49], is as follows:

- D10: A value below which 90% of the sensitivity values lie.

If D10 is positive, there is a 90% likelihood that increasing the input results in an increase in the output.

- D90: A value above which 90% of the sensitivity values lie.

If D90 is negative, there is a 90% likelihood that the output decreases as the input increases.

- D25 and D75: Intermediate sensitivity percentiles that offer additional insight into the variability of sensitivity across the input domain.
- D50: The median sensitivity value, indicating a 50% probability that the output increases or decreases in response to changes in the input.

Inputs with sensitivity distributions clustered near zero have minimal influence on the output, whereas parameters with distributions shifted farther from the zero baseline exert a stronger impact. By comparing percentile values and their spacing, the relative importance of each input variable can be assessed and ranked, offering a clear understanding of the factors that most significantly affect the model's predictions.

Table 2. **Mean relative sensitivity values for liquefaction potential and ground surface settlement with respect to input parameters**

Output	LP					SD				
input	ST	GWL	FP	N_{SPT}	D	ST	GWL	FP	N_{SPT}	D
Relative Mean	-0.818	0.252	-2.48	-1.036	-0.985	0.0847	-0.285	0.253	0.215	-0.019

As discussed earlier, the use of relative sensitivity values rather than absolute values provides a more meaningful basis for comparing the influence of different input variables. Table 2 reports the mean relative sensitivity values of the two output parameters settlement (SD) and liquefaction potential (LP) with respect to the selected inputs.

The statistical percentiles derived for the relative sensitivity values associated with liquefaction potential across all five input variables are illustrated in Figure 18. As shown, more than 75% of the relative sensitivity values associated with soil type (ST) are negative. This indicates that as the soil type index increases, the corresponding liquefaction potential decreases reflecting the improved resistance of higher-quality soil classifications.

For the groundwater level (GWL), most sensitivity values cluster near zero, with a dominance of positive values. This trend suggests that rising groundwater levels contribute to an increased likelihood of liquefaction, which aligns with fundamental geotechnical principles regarding effective stress reduction.

Among all inputs, the fine particle content (FP) exhibits the most pronounced negative relative sensitivity values. This implies that increasing fine content leads to the greatest reduction in liquefaction susceptibility highlighting its substantial mitigating effect on liquefaction potential.

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The remaining variables, including the Standard Penetration Test value (SPT-N) and liquefiable soil depth (D), also display predominantly negative sensitivity values. This indicates that increasing either of these parameters decreases the liquefaction potential, consistent with the sensitivity trends observed across the studied input space.

Based on the collective evidence from Figure 18, the relative distances of percentile categories from the zero baseline, and the mean sensitivity values presented in Table 2, it can be concluded that the fine particle percentage (FP) exerts the strongest influence on liquefaction potential. This makes FP the dominant controlling factor among all evaluated input variables.

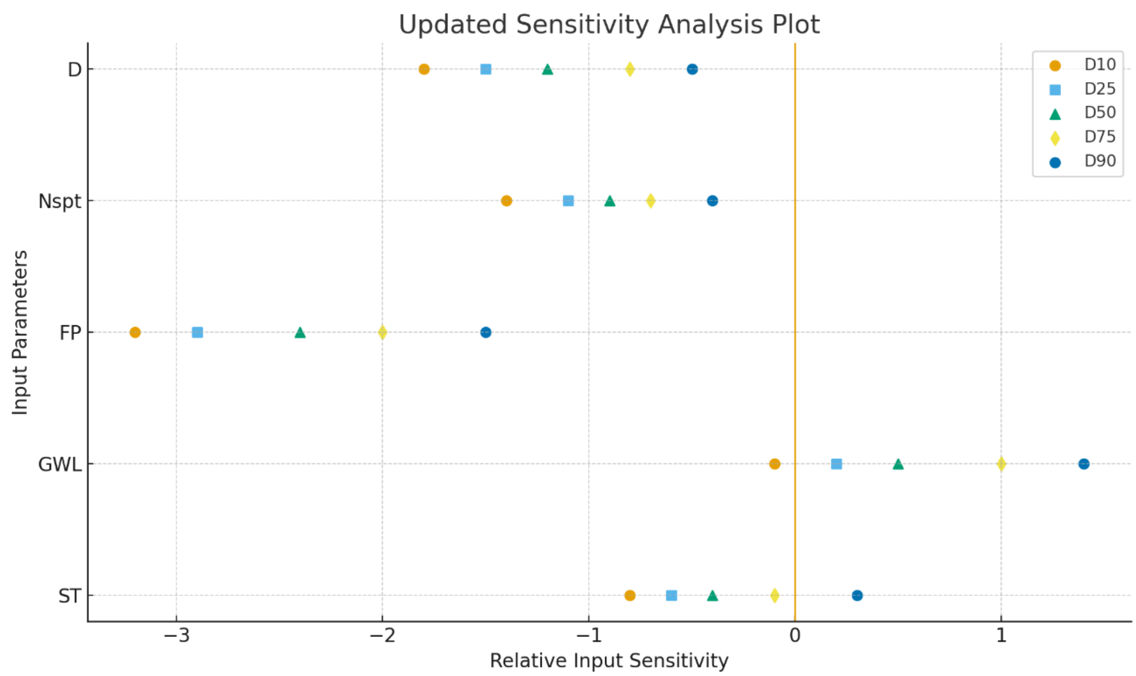

Figure 18. **Sensitivity Analysis of the Deep Learning Method on Input Parameters**

6. Discussion

The findings of this study highlight the effectiveness of integrating advanced artificial intelligence techniques with geotechnical engineering data for predicting liquefaction potential. The superior performance of the CNN–MVO model compared to conventional approaches underscores its ability to capture the nonlinear and multi-dimensional relationships inherent in soil behavior under seismic loading.

The high correlation coefficients (R > 0.90) across all data subsets indicate that the hybrid model successfully generalizes and avoids issues such as overfitting. The low MSE values further confirm the reliability of the model's predictive capability. Additionally, the successful encoding of geotechnical parameters such as soil type and fine content demonstrates that deep learning methods can effectively handle both categorical and continuous variables.

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Sensitivity analysis provided valuable insights into the influence of input parameters on liquefaction susceptibility. Consistent with previous empirical studies, increasing fine content significantly reduces the likelihood of liquefaction, confirming its stabilizing role in sandy soils. The analysis also highlighted the importance of groundwater level and SPT-N, both of which exhibited strong directional impacts on liquefaction potential. Such findings validate the physical consistency of the model and increase confidence in its practical applicability.

Overall, the model's accuracy and interpretability, along with its data-driven foundation, position it as a powerful tool for seismic hazard assessment, especially in regions with limited access to advanced laboratory testing yet abundant in situ geotechnical data.

7. Practical Implications

The proposed CNN–MVO hybrid model provides several practical benefits for geotechnical engineers and decision-makers:

- Improved Risk Assessment: The high accuracy of the model enables more reliable evaluation of liquefaction potential across various soil conditions, reducing uncertainty in seismic design.
- Cost-Effective Analysis: The method relies on readily available field data such as SPT results, making it suitable for projects where advanced laboratory testing is not feasible.
- Enhanced Decision-Making: By identifying the most influential soil parameters particularly fine content, SPT value, and groundwater level the model assists engineers in prioritizing mitigation efforts.
- Adaptability to Local Conditions: The model was trained using regional data from northern Iran, ensuring compatibility with real-world geological conditions and enhancing its usability in similar contexts.
- Support for Design and Planning: The ability to predict both liquefaction potential and settlement assists engineers in designing foundations, embankments, and critical infrastructure with improved seismic resilience.
- Pathway to Smart Geotechnics: This study contributes to the integration of AI-driven tools in geotechnical engineering, paving the way for automated hazard assessment and intelligent site characterization.

8. Conclusions

The present study focused on evaluating one of the most critical hazards in geotechnical and earthquake engineering soil liquefaction by employing soft computing and artificial intelligence based methods. Liquefaction is a complex phenomenon primarily affecting loose, saturated sandy layers, in which cyclic seismic loading increases pore water pressure and causes a significant reduction in effective stress. As inter-particle contacts weaken and shear strength diminishes, the soil mass progressively loses its load-bearing capacity, resulting in excessive deformation, settlement, or even complete structural failure.

The fundamental mechanism of liquefaction involves the progressive buildup of pore pressure triggered by repeated shear stress during earthquake shaking. When the loading rate exceeds

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the rate of pore water dissipation, the soil cannot contract volumetrically, leading to increases in pore pressure and corresponding reductions in effective stress. The magnitude of pore pressure generation is governed by the soil's compressibility, its tendency for volumetric strain under cyclic loading, and the intensity and duration of the applied seismic forces.

To accurately evaluate liquefaction potential, the research methodology was developed as a multi-stage and partially parallel process involving the following steps:

- Comprehensive identification of liquefaction hazards and conventional evaluation methods.
- Assessment and analysis of liquefaction susceptibility in major geotechnical projects across the northern provinces.
- Compilation of a robust dataset for training artificial neural networks and deep learning models.
- Preprocessing and refinement of the database through normalization and outlier removal.
- Selection of meaningful input and output parameters based on commonly performed geotechnical tests.
- Development and coding of a hybrid deep learning model combining Convolutional Neural Networks (CNN) with the Multi-Verse Optimizer (MVO) algorithm.
- Implementation of the hybrid model on the curated dataset.
- Evaluation of model performance using established quantitative indices.

Given the availability of approximately 300 high-quality geotechnical data samples from northern Iran, input parameters were carefully selected to represent the dominant factors influencing liquefaction behavior. These included Soil Type (SP), Groundwater Level (GWL), Fine Percent (FP), SPT blow count (Nspt), and Depth of Liquefiable Soil (D). The two critical outputs Liquefaction Potential (LP) and Estimated Settlement (SD) were chosen due to their engineering importance in seismic design and risk assessment.

Model development, training, and evaluation were conducted using MATLAB 9.5 (2018b), which offers advanced neural network functions, reliable training algorithms, and strong processing capabilities suitable for engineering applications. Model performance was assessed using the Regression Coefficient (R) and the Mean Squared Error (MSE).

8.1 Results and Key Findings

- The hybrid CNN–MVO deep learning model demonstrated excellent predictive performance, achieving a regression coefficient (R) of approximately 90% across training, testing, and validation phases.
- Low MSE values consistently below 0.5 indicate the high accuracy and robustness of the proposed framework.
- Sensitivity analysis revealed that among the five input variables, Fine Content (FP) exerted the greatest influence on liquefaction potential. This was confirmed through percentile-based sensitivity measures, relative mean values, and distribution trends.

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- Other parameters such as SPT value (Nspt), Soil Type (SP), and Depth of Liquefiable Layers (D) exhibited predominantly negative sensitivities, indicating a reduction in liquefaction potential with increases in these variables.
- Groundwater Level (GWL) showed mostly positive sensitivity values, confirming its known contribution to higher liquefaction susceptibility.

9. Novelty and Contribution of the Study

The primary novelty of this study lies in the integration of a deep learning architecture (CNN) with the Multi-Verse Optimization (MVO) algorithm, specifically tailored for liquefaction prediction using real-world geotechnical data. Unlike traditional empirical or semi-empirical liquefaction evaluation methods, the proposed CNN–MVO hybrid framework:

- Learns complex nonlinear relationships between soil properties and liquefaction behavior.
- Reduces dependence on empirical correlations that may not be universally applicable across diverse geological settings.
- Offers enhanced predictive accuracy through model optimization driven by MVO's exploration–exploitation mechanics.
- Updates liquefaction risk predictions based on data-driven learning rather than simplified deterministic factors.
- Provides a clear interpretation of variable influence through derivative-based sensitivity analysis addressing the well-known "black-box" challenge associated with deep learning models.

This study demonstrates that by leveraging advanced AI techniques in combination with extensive geotechnical datasets, it is possible to achieve significantly more reliable evaluations of liquefaction potential. The findings hold substantial value for seismic hazard mitigation, improved geotechnical design, and risk-informed decision-making in regions with high liquefaction susceptibility, including the northern provinces of Iran.

10. FUTURE WORK

Future research should focus on expanding the database to include additional geotechnical and seismic parameters such as shear wave velocity (Vs), CPT tip resistance (qc), and cyclic triaxial test results. Incorporating more diverse datasets from different geological settings can further enhance the model's generalizability.

Moreover, hybrid frameworks integrating CNN with other optimization algorithms such as Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), or Harris Hawks Optimization (HHO) could be explored to improve convergence speed and reduce computational cost.

Another promising direction is the development of real-time liquefaction prediction systems using deep learning models combined with seismic monitoring networks. Additionally, explainable AI (XAI) techniques should be applied to further improve the interpretability of model decisions, especially for safety-critical applications.

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Finally, extending the model to predict other liquefaction-induced effects such as lateral spreading or foundation settlement could significantly expand its usefulness for seismic risk mitigation and infrastructure design.

Author contributions: Shima Aghakakhiri carried out the core components of the research, including data collection, preprocessing, numerical modeling, and preparation of the manuscript draft. The foundational idea and project concept were proposed by Dr. Mohammad Emami Koorandeh, who also led the development of the research framework, contributed substantially to the design and implementation of the machine learning models, interpreted the analytical results, and provided in-depth revisions of the manuscript. His expert guidance and technical insight were instrumental throughout all phases of the study. Dr. Ghodratollah Mohammadi and Dr. Amir Taban reviewed the final version of the manuscript and contributed general academic feedback.

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Conflicts of interest: The author declares that there is no conflict of interest.

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