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Rediction of Liquefaction in Sandy Soils Using Deep Learning Methods

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ABSTRACT

This study investigates various deep learning algorithms such as fuzzy networks and k-nearest neighbors for predicting the liquefaction or non-liquefaction behavior of soil. Since soil liquefaction causes severe damage to infrastructures and lifelines, predicting this phenomenon is crucial. Two machine learning approaches were compared in this research to evaluate their effectiveness in predicting soil liquefaction. The models were constructed with multiple input parameters and a single output (liquefaction/non-liquefaction) under seismic conditions with a magnitude of 7.8. Model performance was assessed based on CPT (Cone Penetration Test) data using accuracy metrics in three states (liquefied, non-liquefied, and overall) along with confusion matrices and ROC (Receiver Operating Characteristic) curves. The study utilized models such as K-Nearest Neighbors (KNN) and fuzzy networks to evaluate soil liquefaction potential.

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Introduction

Significant structural damage due to liquefaction-induced settlement or tilting—such as the 1995 Kobe earthquake or the 1906 San Francisco earthquake—has long posed concerns in geotechnical engineering. Early experimental methods evolved with the advancement of precision tools and artificial intelligence-based approaches, such as deep learning. In 1996, Zadeh introduced fuzzy rule-based systems, which are now widely used in science and technology [1]. These systems provide a framework for dealing with imprecise and ambiguous data inputs and responses [2]. In recent years, fuzzy logic has also found applications in structural engineering [3] and slope failure risk mapping [4]. Various researchers from 2022 to 2025 have explored the use of KNN, fuzzy logic, and hybrid methods to predict liquefaction potential [5–16].

CPT-Based Soil Evaluation

In-situ tests like CPTu and SPT are used to determine safety factors for further laboratory analysis. CPT is especially favored for its continuous and high-resolution data. Although it cannot directly identify soil type across the depth profile, integrating it with shear wave velocity (Vs) tests can overcome this limitation. Tests such as cyclic triaxial and simple shear tests are employed to reproduce in-situ dynamic stress conditions using SPT or CPT data. According to national technical construction standards (NTC18), assessing liquefaction potential during the design phase is critical. Liquefaction curves based on corrected tip resistance (qc1N) and fine content (FC) help define the CRR (Cyclic Resistance Ratio) and CSR (Cyclic Stress Ratio), essential for triaxial testing. Boulanger and Idriss (2014) proposed adjustments for clean sand correlations [19].
Figure 1
Evaluation of soil liquefaction potential based on CPT and boundary curves recommended for soils with different fines content (FC) [19].

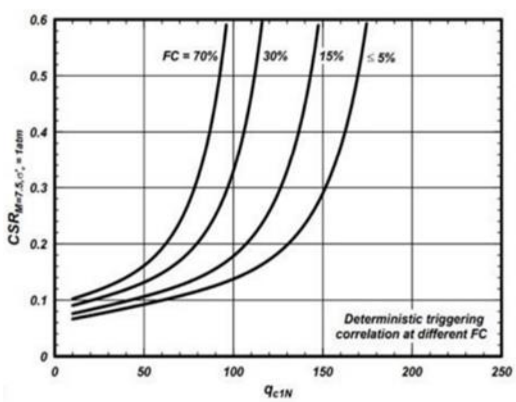

Figure 1 . Evaluation of soil liquefaction potential based on CPT and recommended boundary curves for soils with different fines content (FC) [19].

Deep Learning and Machine Learning Models

1. Deep Learning Framework

Machine learning (ML) models, a subset of artificial intelligence, are categorized into supervised, unsupervised, and reinforcement learning. In supervised learning, the target variables are known—applicable to this study, as the liquefaction outcome is binary. Therefore, classification algorithms were utilized. By testing various algorithms, the most effective can be identified based on the quality and interrelation of features. This study used ML to distinguish liquefied and non-liquefied conditions and to explore nonlinear patterns using models like KNN and fuzzy neural networks.

2. K-Nearest Neighbors (KNN)

KNN is a supervised classification and regression algorithm. It predicts a data point's class by majority voting among its k nearest neighbors. In this study, KNN was applied to classify soil samples as liquefiable or not. The algorithm is known for its versatility and simplicity in various classification tasks [21].

3. Fuzzy Neural Network

A fuzzy system comprises a knowledge base with fuzzy rules and a database defining linguistic variables for inputs and outputs. Fuzzification converts inputs to fuzzy values based on their membership functions. The inference engine evaluates rule activation levels and computes fuzzy outputs. Finally, defuzzification transforms fuzzy results into crisp outputs [6].

Application of Deep Learning Methods

The input parameters were selected to best represent soil behavior. Around 130 data samples were gathered from geotechnical studies along Iran's northern coastline. A seismic magnitude greater than 7 (Mw > 7) was considered for modeling. MATLAB R2016a was used for coding and implementation.

Results of Machine Learning Models

Liquefied soils lose strength and behave like fluids during earthquakes, threatening infrastructure and lives. Traditional prediction methods can be time-consuming and require extensive data. Deep learning provides a powerful alternative. The CPT-based models were assessed in MATLAB, with accuracy, precision, recall, and F-measure evaluated for liquefied, non-liquefied, and overall classifications. Two ensemble models were constructed for comparison.

F-measure	Recall	Precision	Accuracy (ALL)	Accuracy (Non.Liq)	Accuracy (Liq)	Name of Deep Learning Model	Row
0,432	0,50	0,380	0,684	0,50	0,743	KNN	1
0,8	0,909	0, 714	0,887	0,909	0,880	Fuzzy	2

Table 1 . Confusion Matrix Results for 80-20 Train-Test Split

The accuracies of psychrotrophic (psychrotroph) and non-psychrotrophic classes, as well as the overall accuracy obtained from each model, are shown in the table. As presented in Table 1, the accuracy for the psychrotrophic class is 74.3% for the K-Nearest Neighbors (KNN) model and 88.0% for the fuzzy network model. For the non-psychrotrophic class, accuracies are 50.0% for KNN and 90.9% for the fuzzy network model. The overall accuracy is 68.4% for KNN and 88.7% for the fuzzy network model. It can be concluded that the fuzzy network model predicts soil psychrotrophy more accurately than the KNN model.

Selecting the most effective machine learning algorithms for predicting soil psychrotrophy sensitivity requires robust evaluation. The choice of appropriate performance metric(s) depends on the specific context of the psychrotrophy prediction problem. Accuracy and F-measure may provide a more comprehensive overview of model performance for a balanced dataset. Researchers and engineers can effectively evaluate and compare ML algorithms for predicting soil psychrotrophy sensitivity by considering a combination of these metrics along with ROC-AUC.
In Figures 2 and 3, the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) is calculated to quantify each classifier's performance. A higher AUC indicates better performance, with the numerical value 1 representing a perfect classification. ROC-AUC was chosen for this study because it evaluates classifier performance across different classification thresholds, making it especially useful in this context. This is particularly important in soil psychrotrophy prediction, where correctly identifying both psychrotrophic and non-psychrotrophic states is crucial. According to the observations noted, the ROC curve for the fuzzy network shows better performance than that of the K-Nearest Neighbors model.

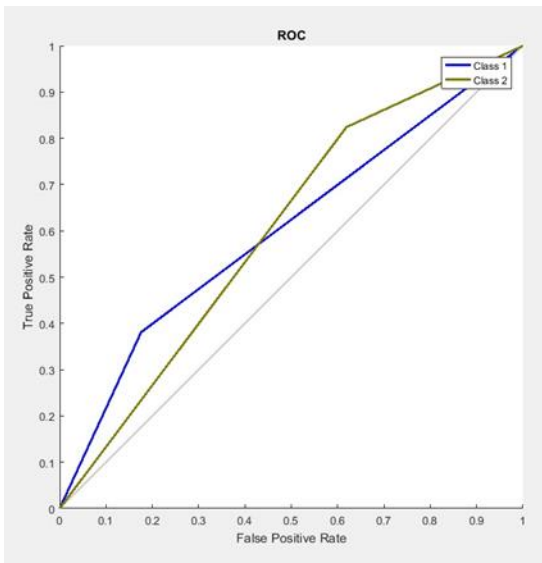

Figure 2. ROC curve for KNN model

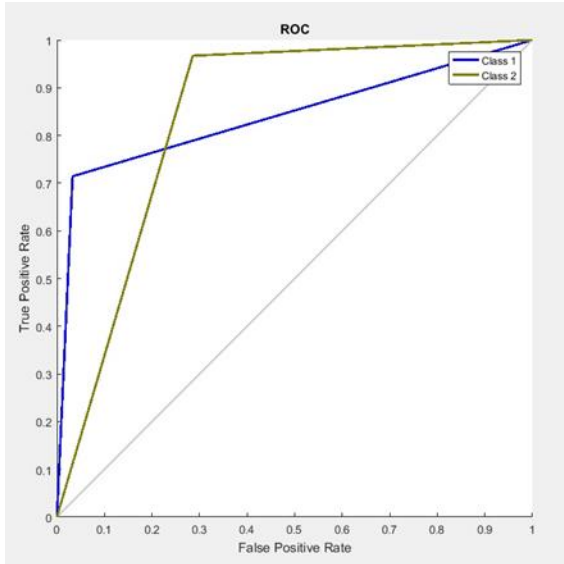

Figure 3. ROC curve for Fuzzy model

In figuris 4 ad 6, diagrammata quae accuratitudines (%) classium psychrotrophiae, classis non psychrotrophiae, et status generalis ex metodis usus machinarum exhibent demonstrantur

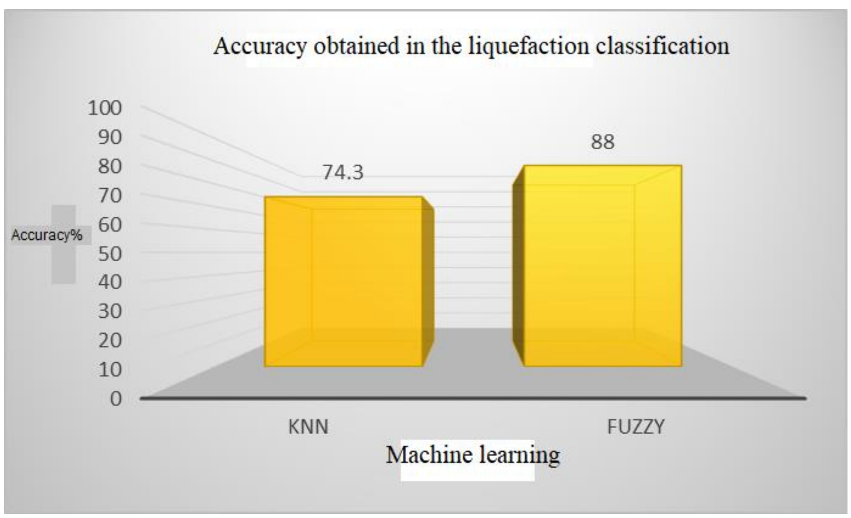

Figure 4. Liquefied class accuracy comparison between models

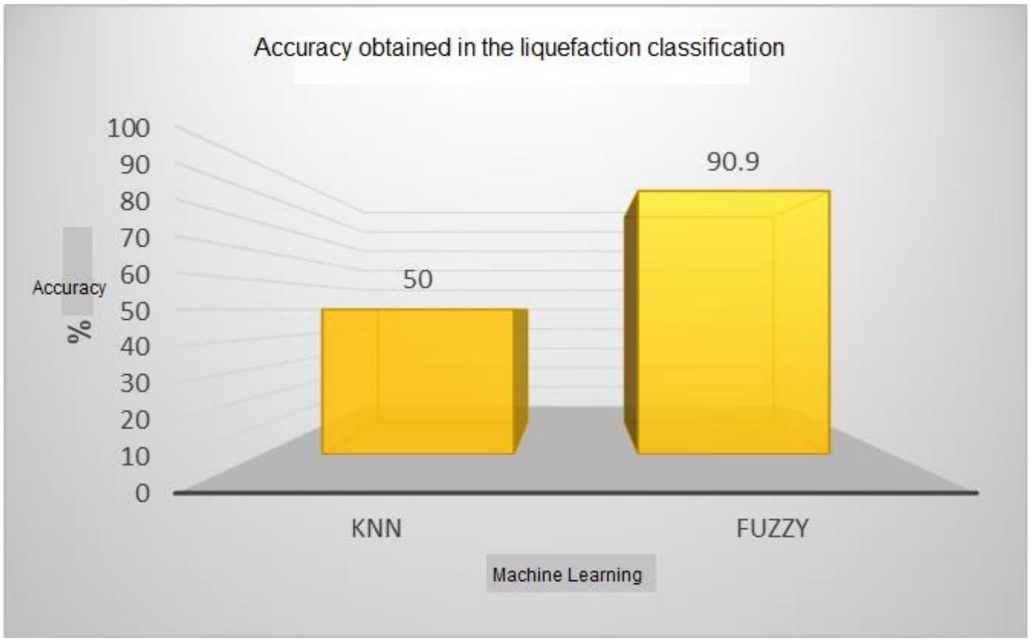

Figure 5. Non-liquefied class accuracy comparison

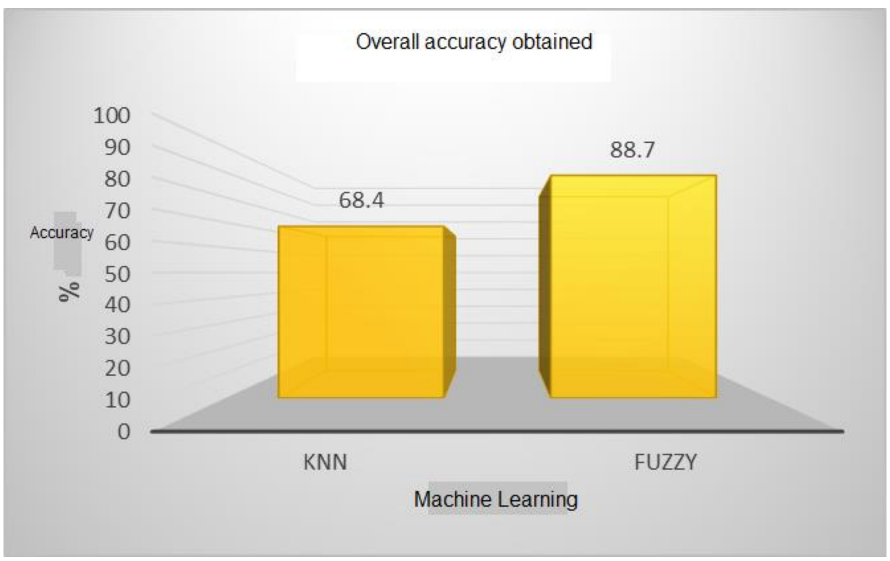

Figure 6. Overall accuracy comparison

Conclusion

This study compared two machine learning models—KNN and fuzzy logic—for predicting soil liquefaction under seismic conditions (Mw = 7.8). Input data were derived from CPT results. The fuzzy model achieved 88% accuracy in the liquefied class, 90.9% in the non-liquefied class, and 88.7% overall. KNN achieved 74.3%, 50.0%, and 68.4%, respectively. The ROC curve further supported the fuzzy model's superiority. Future studies can include a wider range of seismic and soil parameters, incorporate shear wave velocity (Vs) and SPT data, and develop hybrid models for improved performance.

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