

**Title:** Machine Learning for Assessing Soil Liquefaction Risk in Seismic Zones

**Introduction:**

Earthquakes and their associated dynamic loads pose significant risks to structures worldwide. Among the various consequences of seismic activity, liquefaction stands out as a critical secondary effect, particularly in medium to fine-grained saturated granular soils. Liquefaction occurs when soil loses its strength and behaves like a liquid due to increased pore water pressure and reduced effective stress during undrained cyclic loading. This process renders the soil incapable of supporting structures, leading to their sinking and potential collapse. Notably, liquefaction can be triggered not only by earthquakes but also by other sources of cyclic loading such as ocean waves, wind, or machine vibrations.

While the term "liquefaction" was coined relatively recently, its conceptual roots trace back to early attempts to understand soil behavior under shear stress. However, the complexity of the phenomenon, coupled with variations in critical void ratios and loading conditions, necessitates further investigation.

The urgency of studying liquefaction became apparent after catastrophic earthquakes, such as those in Niigata, Alaska, Loma Prieta, Kobe, Kocaeli, and Chi-Chi. These events resulted in widespread damage to infrastructure, including buildings, embankments, slopes, and bridges, highlighting the dire need for research to mitigate liquefaction-induced hazards.

The recent Kahramanmaraş-Türkiye Earthquakes further underscored the destructive potential of liquefaction, with observed manifestations including soil boils, lateral spreading, excessive settlements, bearing capacity failures, and building collapses. Given the substantial threats posed by liquefaction to both lives and infrastructure, intensified research efforts are imperative to develop effective mitigation strategies.[1]



Figure 1 An extreme case of liquefaction-induced bearing capacity failure and toppling of a residential building [1]

This research aims to address the challenges of liquefaction geotechnically by leveraging machine learning (ML) techniques. By analyzing historical earthquake data and geotechnical parameters, ML can predict liquefaction susceptibility with greater accuracy, facilitating informed decision-making in foundation design and soil improvement. This approach holds promise for minimizing the detrimental effects of liquefaction-induced damage on infrastructure.

Geotechnical engineering, which focuses on the behavior of Earth materials and their interaction with structures, traditionally relies on theoretical models and empirical methods. However, the inherent complexity and variability of geological formations often limit the accuracy of predictions. The integration of artificial intelligence (AI), particularly ML and deep learning (DL), presents a transformative opportunity to overcome these challenges.

In recent decades, AI has become increasingly indispensable across various engineering disciplines, including geotechnical engineering. Its applications span diverse sub-disciplines such as frozen soils, rock mechanics, slope stability, foundations, tunnels, dams, and unsaturated soils. By harnessing the power of AI, geotechnical engineers can enhance their understanding of soil behavior and improve the resilience of infrastructure against seismic hazards like liquefaction.[2]

Although the implementation of ML techniques in the evaluation of liquefaction has started since the beginning of the 1990's the prediction models using DL techniques are not common; since DL models need large data sets to function properly and getting huge data sets can be a problem referring to the required data type. despite this problem, some researchers have successfully implemented DL like the study by :

**1. Zhang et al. (2021):[3]**

- Proposed a deep neural network (DNN)-based model for predicting soil liquefaction.
- Incorporated shear wave velocity ( $V_s$ ) and standard penetration test (SPT) data to enhance prediction accuracy.
- Demonstrated high accuracy in liquefaction prediction, especially with the inclusion of  $V_s$  data.
- Recommended further studies to improve model performance by incorporating additional parameters and increasing dataset size.

**2. Kumar et al. (2021):[4]**

- Introduced a novel DL methodology for classifying soil liquefaction.
- Compared DL models with emotional backpropagation neural network (EmBP).
- Utilized cone penetration test data, with cone resistance ( $q_c$ ) and peak ground acceleration (PGA) as inputs.
- Achieved excellent performance compared to EmBP, validated using global earthquake data.
- Suggested further exploration of DL and EmBP techniques in various civil engineering applications.

**3. Kumar (2023):[5]**

- Utilized advanced ML models (DNN, CNN, RNN, LSTM, BiLSTM) to assess liquefaction triggering.
- Trained and tested models using 834 case histories of post-liquefaction data.
- Used two independent variables,  $N_{1,60}$  and CSR, to predict the probability of liquefaction.

- RNN model outperformed others, achieving high coefficient of determination ( $R^2 = 0.906$ ) during testing.
- Recommended further steps to enhance model accuracy, including training on larger datasets, comparison with standard models, and validation through laboratory experiments.

Each study contributes to the advancement of soil liquefaction prediction models, addressing challenges such as data availability and model accuracy. Additionally, they highlight the importance of incorporating various parameters and employing advanced ML and DL techniques for more reliable predictions in civil engineering applications.

In this project, a DL approach will be used to determine liquefaction susceptibility using SPT, CPT, and Vs data sets while incorporating more parameters.

### **Conclusion:**

In conclusion, there is a pressing need to address liquefaction hazards in geotechnical engineering, particularly in the wake of seismic events. Through a thorough examination of historical earthquakes and their devastating impact on infrastructure, it becomes evident that liquefaction poses significant risks to structures worldwide. The review emphasizes the transformative potential of machine learning (ML) and deep learning (DL) techniques in advancing liquefaction prediction models, despite challenges such as data availability and model accuracy. Recent studies have shown promising results by integrating ML and DL methodologies and emphasizing the importance of incorporating various parameters to enhance prediction accuracy. Looking ahead, further research is warranted to expand datasets, incorporate additional parameters, compare different ML and DL techniques, and validate models through laboratory experiments. By leveraging AI technologies, geotechnical engineers can gain deeper insights into soil behavior, leading to more informed decision-making in foundation design and soil improvement, ultimately enhancing resilience and minimizing the detrimental effects of liquefaction on lives and infrastructure globally.

### **References:**

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