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

1. Introduction:

Soil liquefaction poses significant risks to infrastructure and human safety during seismic events. The accurate prediction of liquefaction susceptibility is crucial for mitigating these risks and designing resilient structures. This technology review focuses on deep learning (DL) techniques for soil liquefaction prediction, aiming to explore their potential to improve prediction accuracy and address longstanding challenges in traditional methods. Understanding the significance of DL in this context is essential for advancing geotechnical engineering practices and enhancing infrastructure resilience.

2. Technology Overview:

Deep learning, a subset of artificial intelligence, utilizes neural networks with multiple layers to extract intricate patterns from large datasets. Its purpose in soil liquefaction prediction is to analyze complex geotechnical data, including soil properties and seismic parameters, to accurately assess liquefaction susceptibility. Key features of DL include its ability to capture non-linear relationships within data and its capacity to learn from diverse datasets. DL is commonly used in geotechnical engineering for tasks such as soil classification, landslide prediction, and liquefaction assessment.

3. Relevance to the Project:

DL techniques are relevant to our project as they offer a promising approach to addressing the challenges associated with soil liquefaction prediction. By leveraging large datasets and complex data patterns, DL models can enhance prediction accuracy and improve risk management strategies. Incorporating DL into our research can contribute to the success of our project by providing more reliable liquefaction susceptibility assessments and informing engineering decisions in earthquake-prone regions.

4. Comparison and Evaluation:

Compared to traditional methods, DL offers superior accuracy and reliability in soil liquefaction prediction. While DL models require substantial computational resources and expertise, their performance justifies the investment, especially in critical applications like liquefaction prediction. Factors such as cost, ease of use, scalability, and performance must be considered when evaluating DL techniques for our project.

5. Use Cases and Examples:

Several studies have successfully applied DL models for soil liquefaction prediction. For example, Zhang et al. (2021) demonstrated the effectiveness of a deep neural network model in incorporating shear wave velocity data for liquefaction prediction. Similarly, Deepak Kumar et al. (2021) proposed a DL-based methodology for classifying soil liquefaction, achieving excellent performance compared to traditional methods. While Kumar 2023 exterminated several DL techniques demonstrating the superiority of RNN. A comparison of the DL techniques has been shown in *Table 1*.

Table 1 comparison of the existing DL models

Study by	Model	Test Type	Number of Inputs	Inputs	Number of Layers	Activation function	Loss function	optimizer	Performance Metric
Zhang et al. (2021)[1]	DL: ML-FCN	SPT & Vs	8	*(z)*, (*FC*), (*N*1,60), *σv*), (*σ*′*v*), (*amax*), Vs and (*Mw*)	9 Dropout (4)	ReLu	BCE	adam	Accuracy 89% 92% 93%
Kumar et al. (2021)[2]	DL	CPT	2	qc, PGA	-	sigmoid	BCE	adam	Precision–Recall F measure 0.73, 0.65
D.R.Kumar et al (2023)[3]	DNN	SPT	7	*(z)*, (*FC*), (*N*1,60), *σv*), (*σ*′*v*), (*amax*), and (*Mw*)	2 hidden layers	ReLu	MAE	adam	Total rank 52
	CNN								55
	RNN								70
	LSTM								16
	BILSTM								47

- Cone Resistance(qc),
- Peak Ground Acceleration (PGA)
- depth (*z*),
- fine content (*FC*),
- corrected SPT count (*N*1*,*60),
- total stress (*σv*),
- effective stress (*σ*′*v*),
- peak horizontal acceleration (*amax*),
- Shear wave velocity (Vs)
- magnitude of the earthquake (*Mw*)
- BCE: Binary Crossentropy
- MAE**:** Mean Absolute Error

6 Gaps and Research Opportunities:

Despite its advancements, DL faces challenges such as data scarcity and model interpretability. Customizations and improvements tailored to specific geotechnical contexts are necessary to optimize DL's effectiveness further. Future research can focus on expanding dataset sizes, exploring additional parameters, and enhancing model interpretability to address these gaps.

7. Conclusion:

In conclusion, deep learning techniques offer significant potential for improving soil liquefaction prediction, thereby enhancing infrastructure resilience and mitigating seismic risks. By leveraging DL's capabilities and addressing existing challenges, our project can benefit from more accurate liquefaction susceptibility assessments and informed decision-making in geotechnical engineering practices.

1. References:

[1] Y. Zhang, Y. Xie, Y. Zhang, J. Qiu, and S. Wu, "The adoption of deep neural network (DNN) to the prediction of soil liquefaction based on shear wave velocity," *Bull. Eng. Geol. Environ.*, vol. 80, no. 6, pp. 5053–5060, 2021.

[2] D. Kumar, P. Samui, D. Kim, and A. Singh, "A Novel Methodology to Classify Soil Liquefaction Using Deep Learning," *Geotech. Geol. Eng.*, vol. 39, no. 2, pp. 1049–1058, 2021.

[3] D. R. Kumar, P. Samui, A. Burman, W. Wipulanusat, and S. Keawsawasvong, "Liquefaction susceptibility using machine learning based on SPT data," *Intell. Syst. with Appl.*, vol. 20, no. June, p. 200281, 2023.