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Machine Learning for Assessing Soil Liquefaction Risk in Seismic Zones

by :
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Project Description

- Risk management project
- Directly relevant to SDG 11 (Sustainable Cities and Communities)

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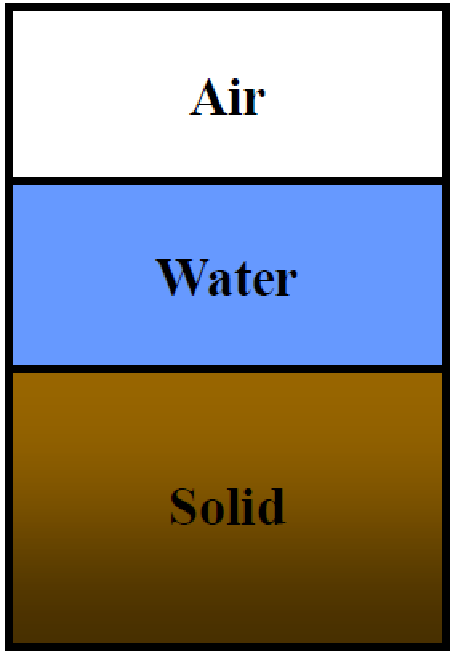
Goals and Objectives

- Building a liquefaction prediction model By analyzing historical earthquake data and geotechnical parameters
- Using the model as a helping tool in mitigating the risks associated with liquefaction

REPORT NO: METU/EERC 2023-01

Importance and Rationale



Where:
σ≡Total normal stress(F/A)
σ'≡Effective normal stress
u≡Pore water pressure

- **Liquefaction** is the process in which a mass of soil loses its strength and starts to behave like a liquid
- **Need?**
- Severe damages
- Financial burden

Loose sand + HIGH GWT + cyclic loading = u↑ + σ constant

The forms of damage




- Tilting
- Sinking
- Floating
- Lateral movement

IkuoTowhata , GEE , 2008 Springer

Value Propositions

- **Field methods**: SPT, CPT, shear wave velocity
- **Laboratory methods**: triaxial test, cyclic direct simple shear test, centrifuge modeling, shake table test.
- **Analytical methods**
- **Numerical methods**
- **AI methods**

Traditional methods

- Accuracy is limited (because of the complexity of geological formations)

ML Models

- transformative opportunity to overcome the accuracy challenges

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Project Elements

- Data Collection
- Data Processing
  - Feature Engineering
  - Data Normalization
  - Dataset Splitting
- Model Training and Evaluation
  - Deep Learning Model
  - Model Deployment and Monitoring
  - Risk Assessment API

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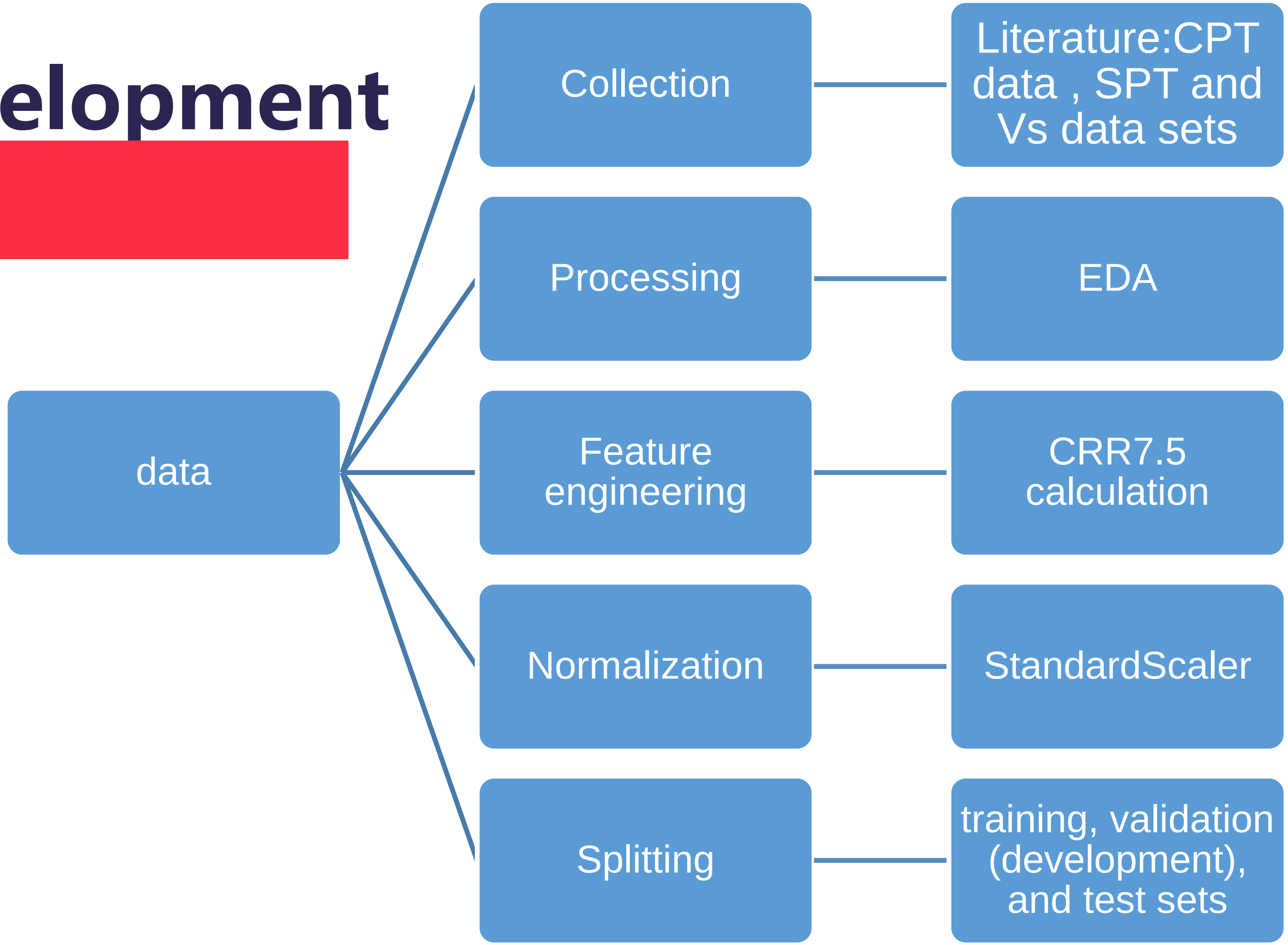
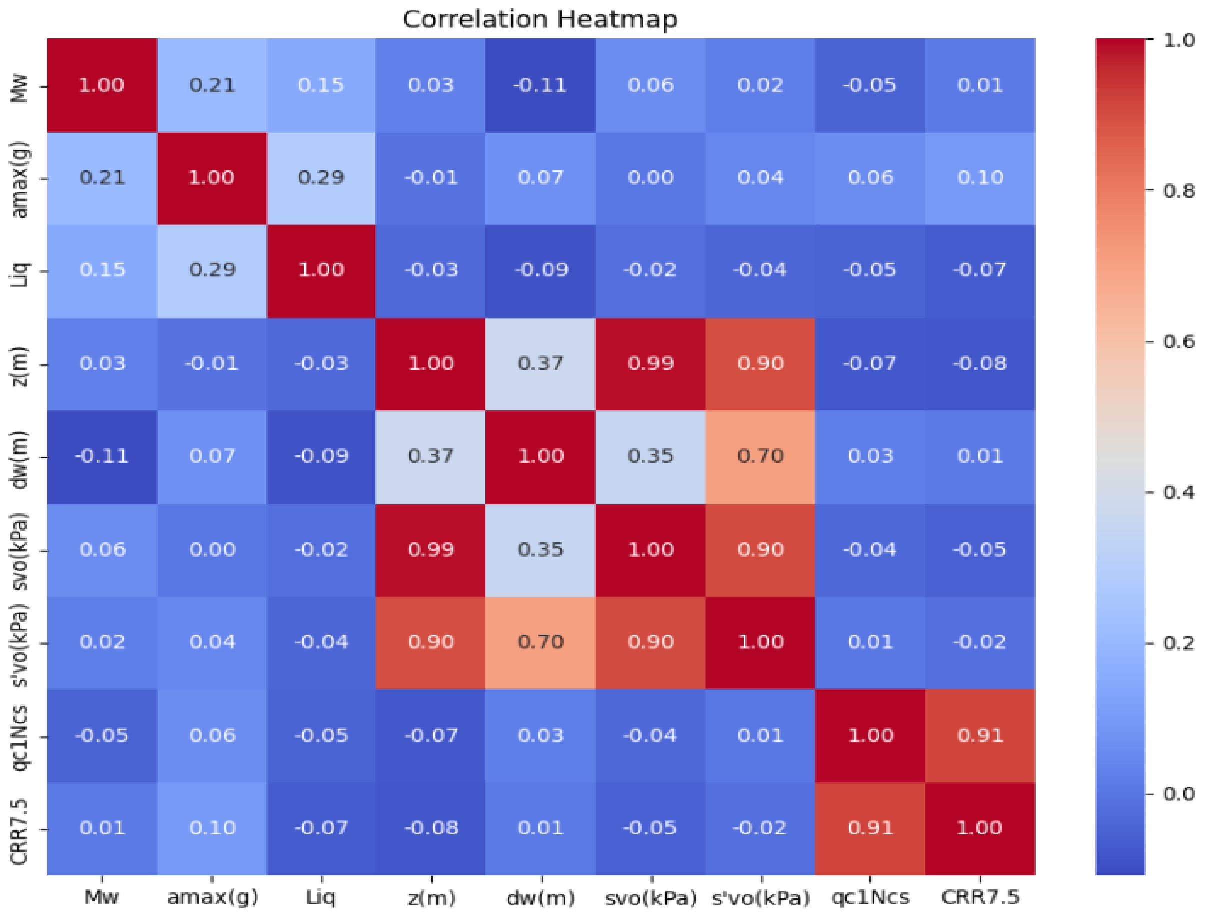
Project Development



Project Development

Table 1 distribution of cases across non-liquefied and liquefied conditions

cases	SPT	CPT	Vs
Non -Liquefied	412	511	505
Liquefied	311	175	585



Project Developmen

- Model
  - training — Deep learning model
  - evaluation — accuracy, precision, recall, F1 score and AUC
  - deployment — gradio

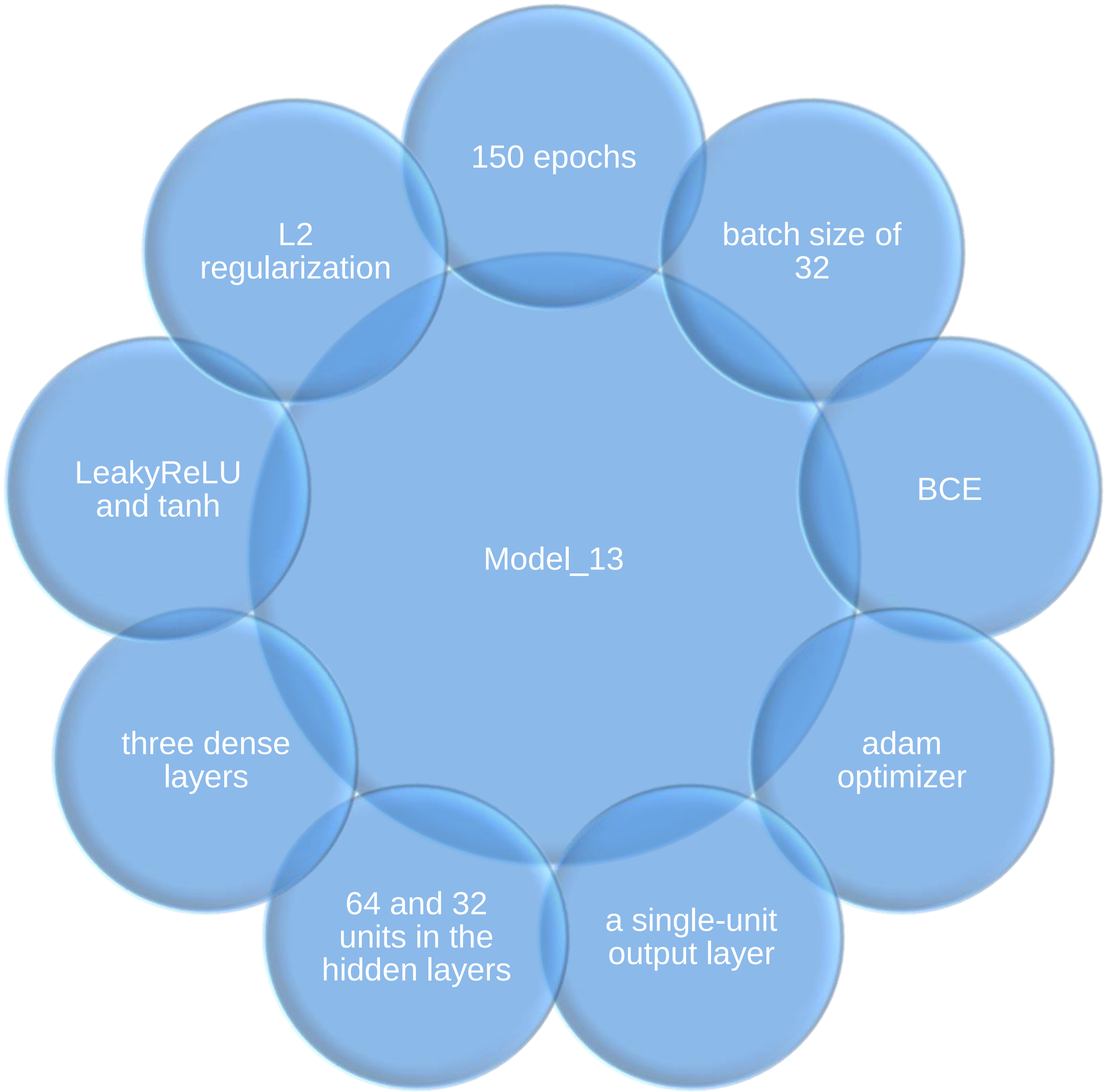
Model Selection

Table 1 qc1Ncs_MODELs evaluation metrics

del	Accuracy (Training)	Precision (Training)	Recall (Training)	F1 Score (Training)	AUC (Training)	Accuracy (Validation)	Precision (Validation)	Recall (Validation)	F1 Score (Validation)	AUC (Validation)	Accuracy (Test)	Precision (Test)	Recall (Test)	F1 Score (Test)	AUC (Test)
el_2	0.9108	0.9063	0.9811	0.9422	0.9686	0.7887	0.8033	0.9423	0.8673	0.7753	0.8889	0.9298	0.9298	0.9298	0.9135
el_3	0.8794	0.8867	0.9599	0.9219	0.9422	0.8028	0.8276	0.9231	0.8727	0.8077	0.8611	0.9123	0.9123	0.9123	0.9404
_12	0.9073	0.9095	0.9717	0.9396	0.9483	0.7746	0.8000	0.9231	0.8571	0.7864	0.8472	0.8966	0.9123	0.9043	0.9193
_13	0.8811	0.8991	0.9458	0.9218	0.9320	0.8028	0.8276	0.9231	0.8727	0.7804	0.8472	0.8966	0.9123	0.9043	0.9263

Model selection

Accuracy (testing)=84.72%



Deployment

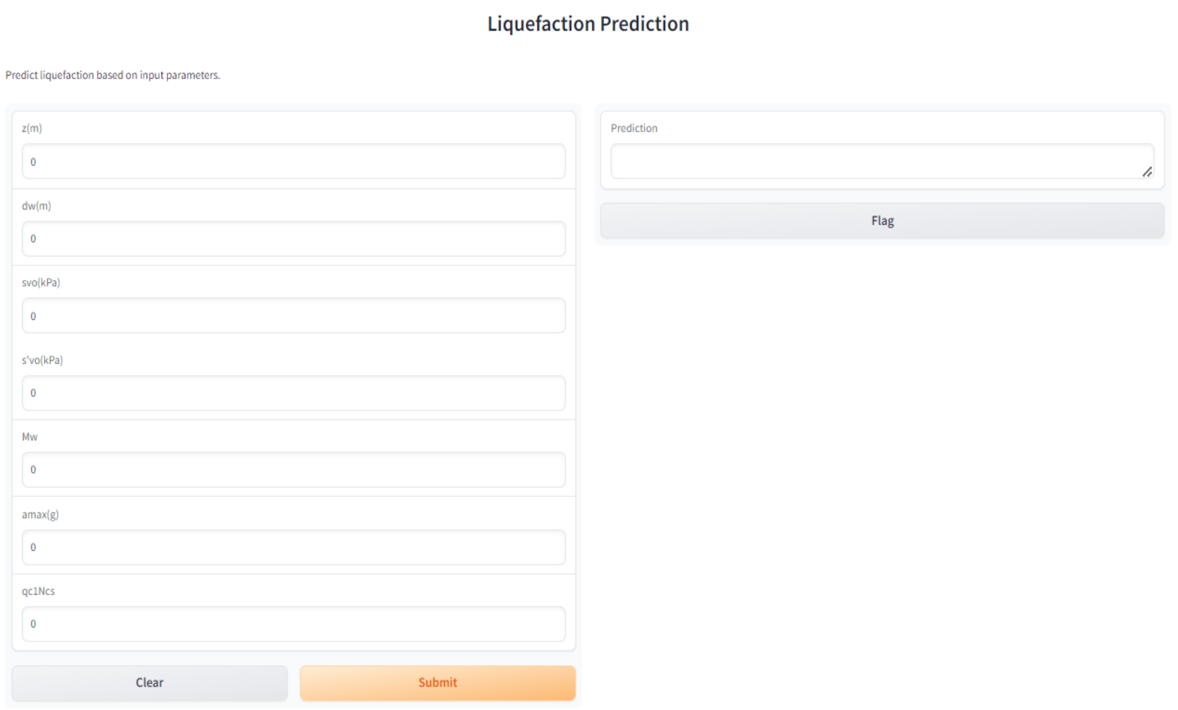


Figure 1 user interface for liquefaction prediction

Conclusion and Futurework

- **1. Enhanced Performance:**
- Refinement and testing phases significantly improved machine learning models for liquefaction susceptibility prediction using CPT data.
- **2. SPT and Vs Models:**
- Deep learning models effectively classify liquefaction potential but show lower accuracy compared to CPT models.
- **3. Future Directions:**
- Focus on exploring alternative algorithms and refining deep learning models for SPT and Vs datasets to enhance predictive accuracy and robustness.

Thank you!