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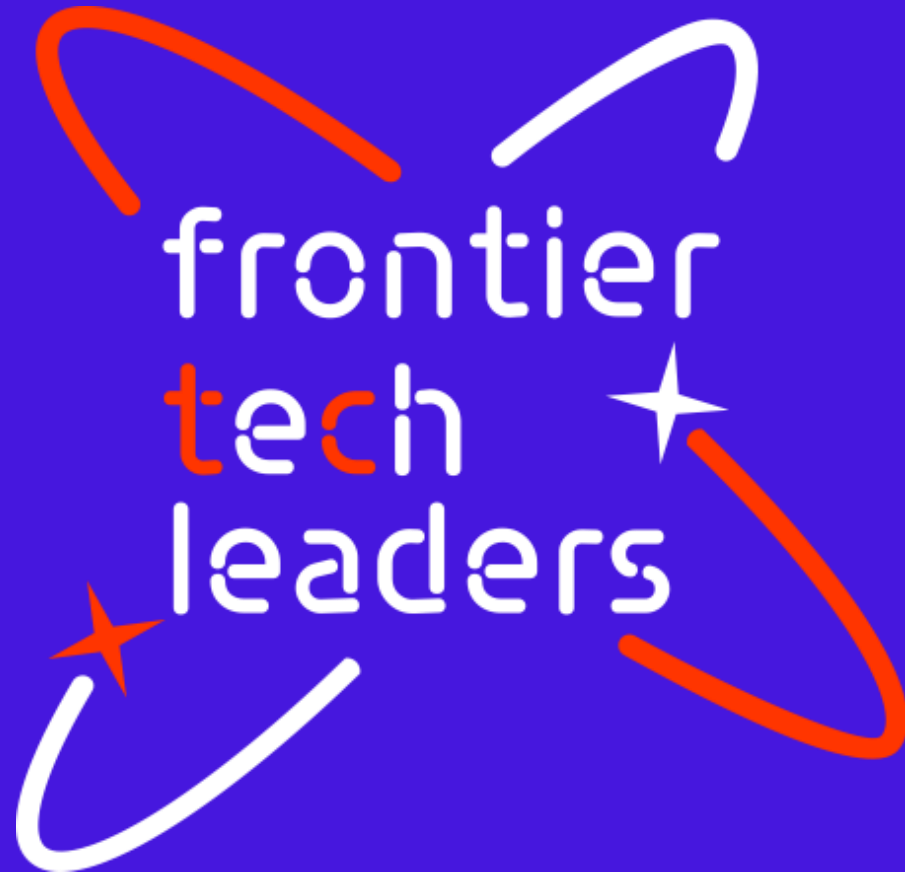
Machine Learning for Assessing Soil Liquefaction Risk in Seismic Zones

by :
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Outline

- Concept note and implementation plan:
 - Background
 - Objectives
 - SDG Relation
- Data
 - Data Collection
 - Exploratory Data Analysis (EDA) and Feature Engineering
- Model Selection and Training
 - Model Evaluation and Hyperparameter Tuning
 - Model Refinement and Testing
- Results
- Deployment
- Future Work



Concept Note and Implementation



Background



Where:

$\sigma \equiv$ Total normal stress (F/A)

$\sigma' \equiv$ Effective normal stress

$u \equiv$ 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



Background



The forms of damage

- Tilting
- Sinking
- Floating
- Lateral movement

Ikuo Towhata , GEE , 2008 Springer

Objectives

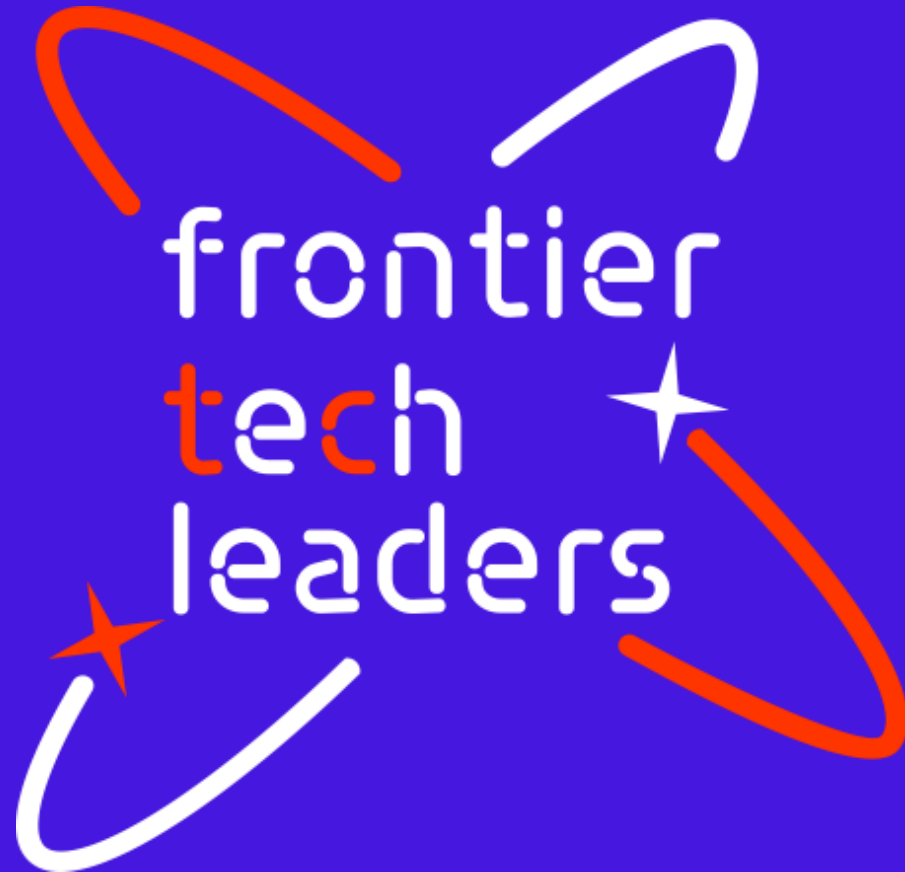
- Building a liquefaction prediction model
By analyzing historical earthquake data
and geotechnical parameters
- Using the model as a helping tool in
mitigating the risks associated with
liquefaction



SDG Relation

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





Data



Data Collection

- Source(s) of the dataset: geotechnical reports, seismic surveys, and academic research papers
- Preprocessing steps during data collection (CPT data sets as an example):
 - Data : five Excel files were imported
 - unique columns specific to individual datasets were removed
 - The datasets were then merged into a single data frame
 - After merging, rows containing any NaN values were dropped

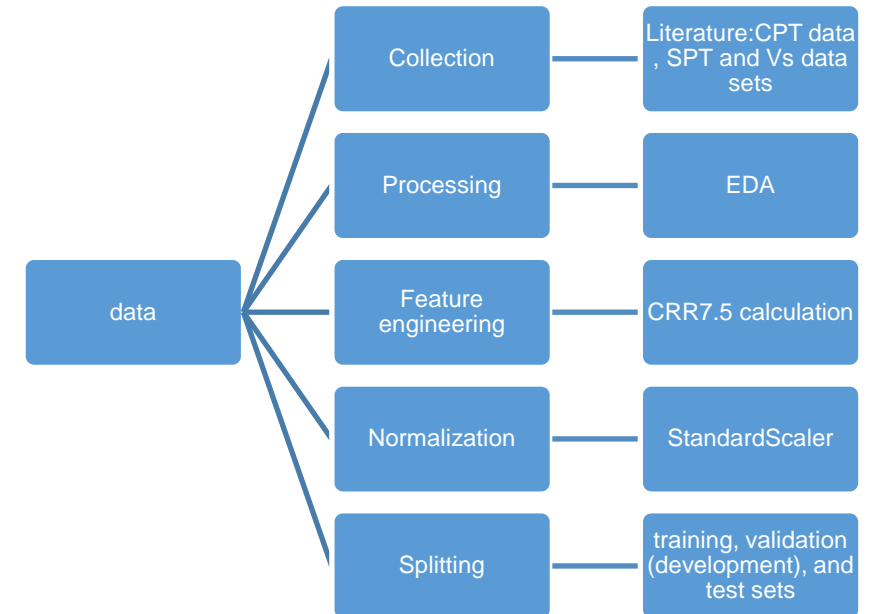


Table 1 distribution of cases across non-liquefied and liquefied conditions

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

Exploratory Data Analysis (EDA) and Feature Engineering

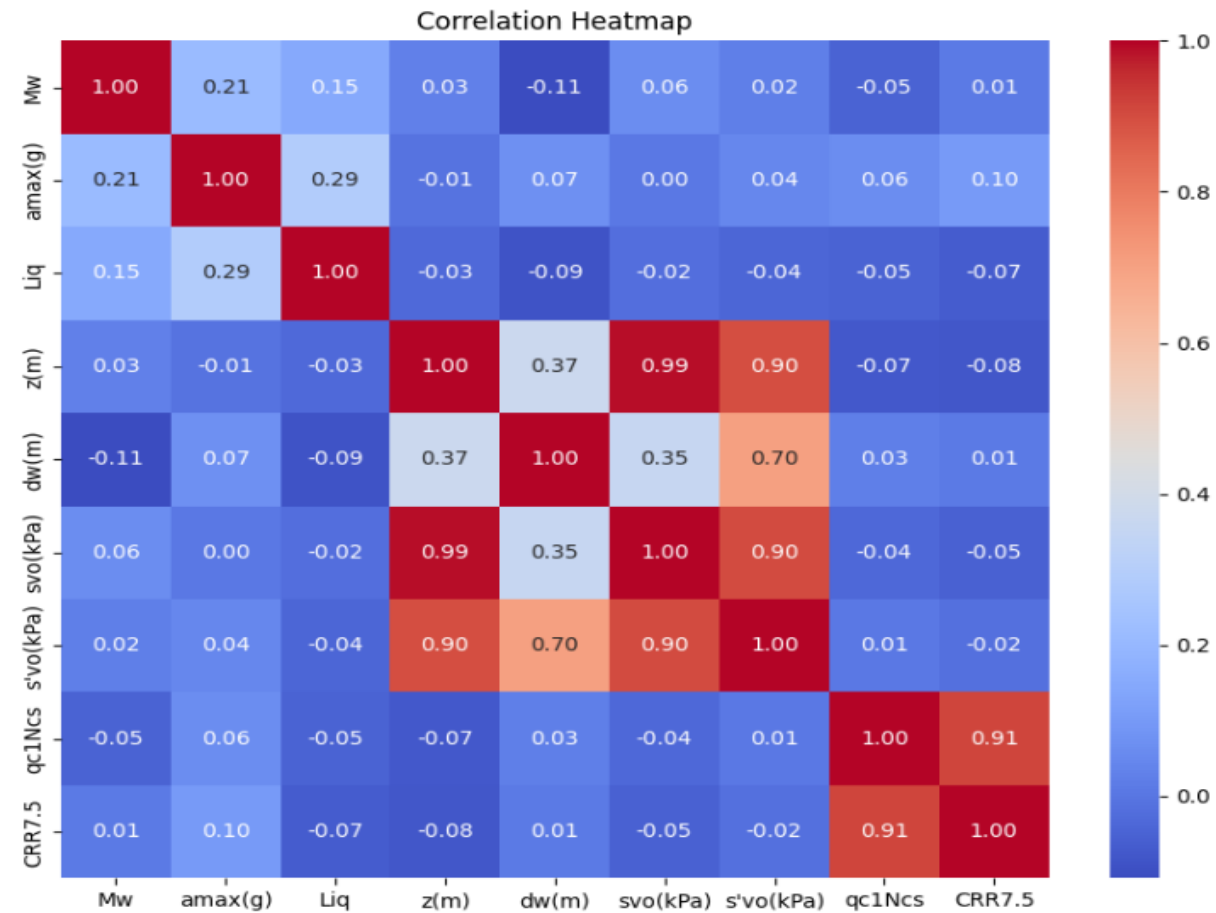
- feature engineering :
 - The calculation of CRR7.5 is based on the IS1893-1, 2016 standard
 - to harmonize data from different soil tests into a common metric

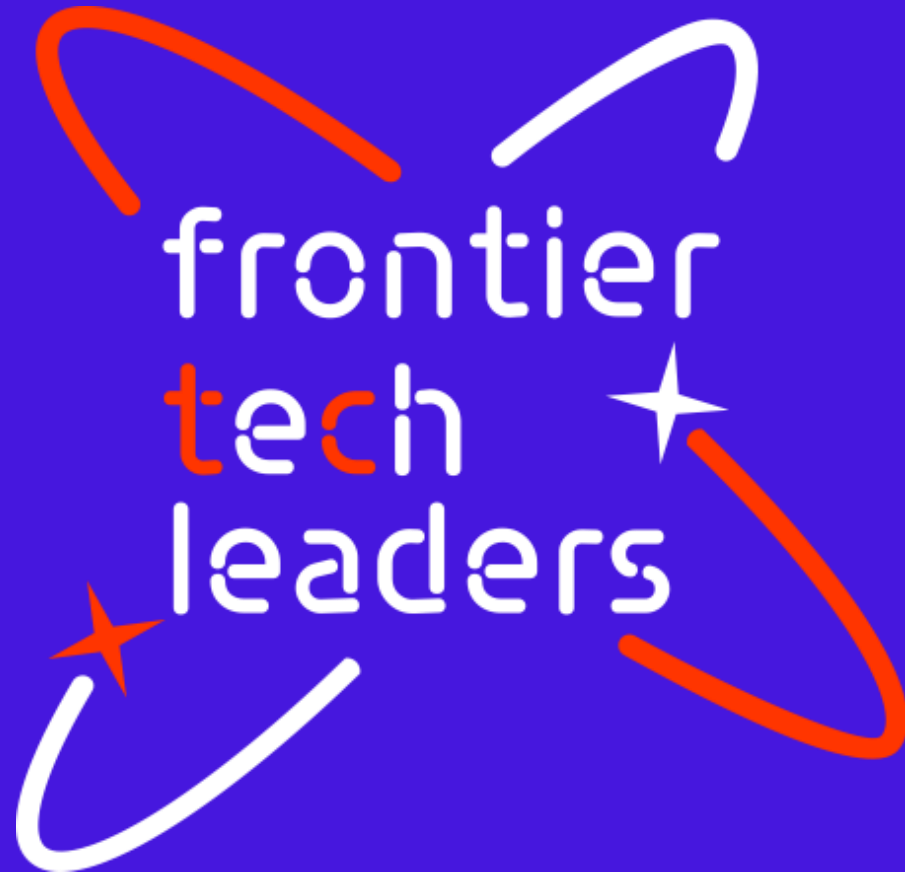
CPT test : ((qC1N)CS

SPT test : (N1)60cs

Vs: test Vs1

- Encoding: transforming the 'Liq' column in `data` from string values ('yes', 'no') to binary numeric values (1, 0).

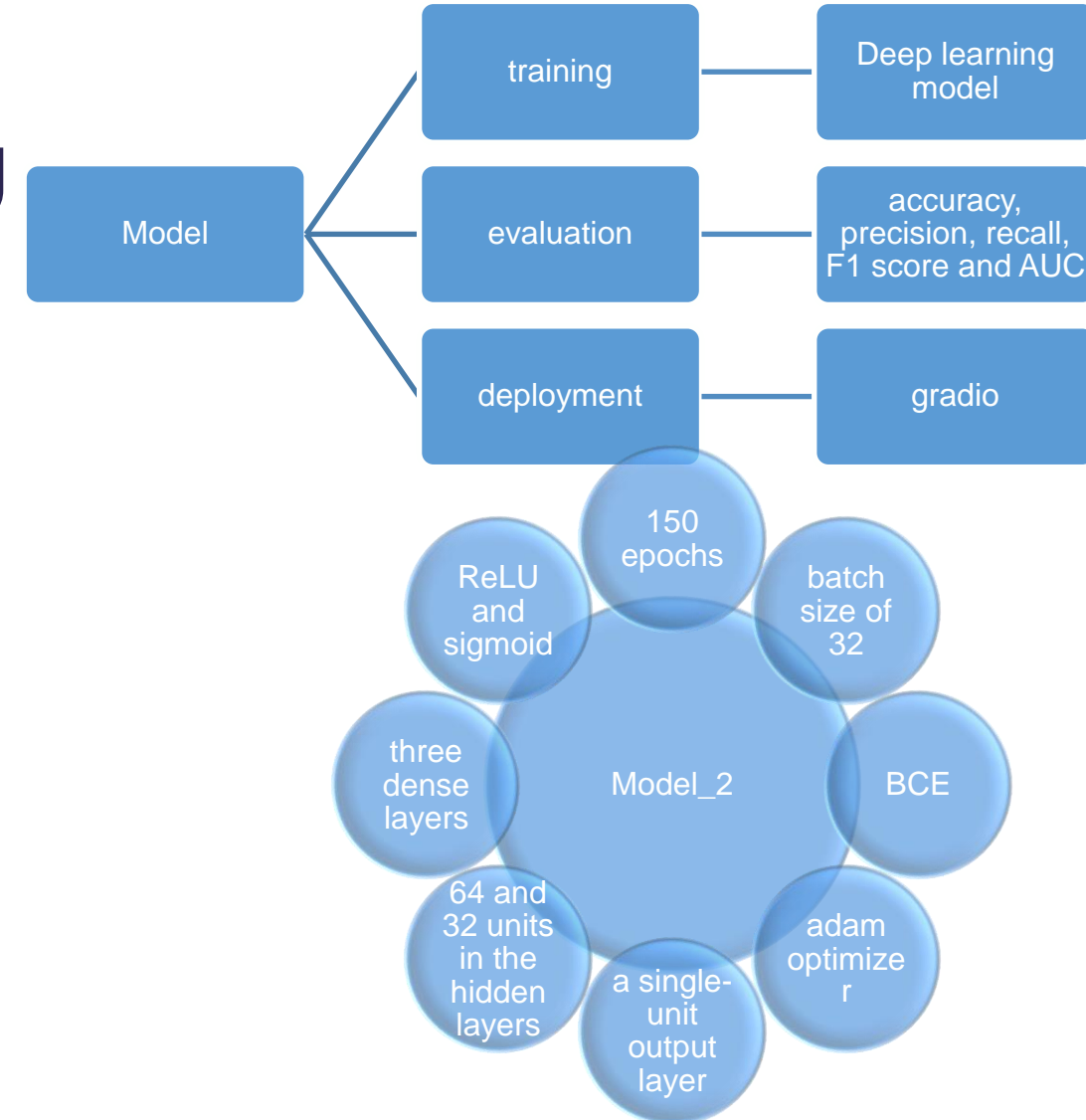




Model



Model Selection and Training



- DL: Compared to traditional methods, offers superior accuracy and reliability ,capture non-linear relationships within data , capacity to learn from diverse datasets , requires substantial computational resources and expertise.
- Details on training the model:model_2
 - i. ReLU and sigmoid activations
 - ii. 3 dense layers , units (64 and 32 units in the hidden layers) ,a single-unit output layer
 - iii. 'adam' optimizer , 'binary_crossentropy' loss function ,batch size of 32 over 150 epochs.

Model Evaluation and Hyperparameter Tuning

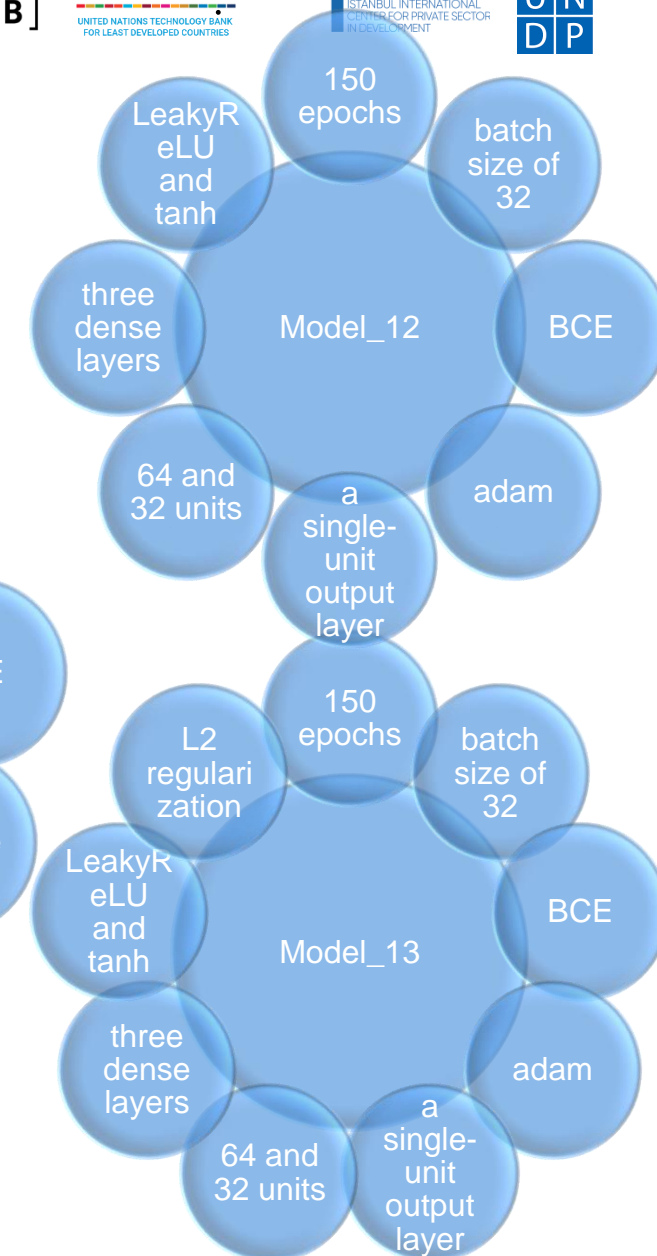
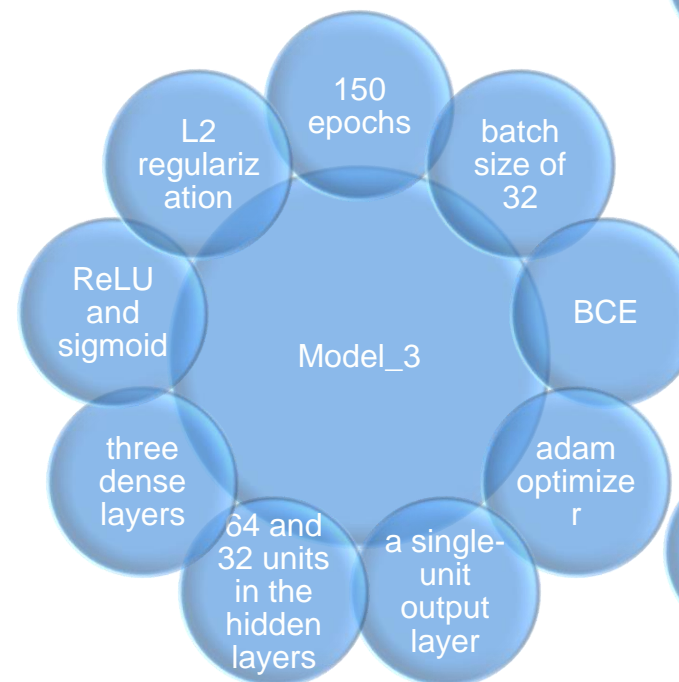


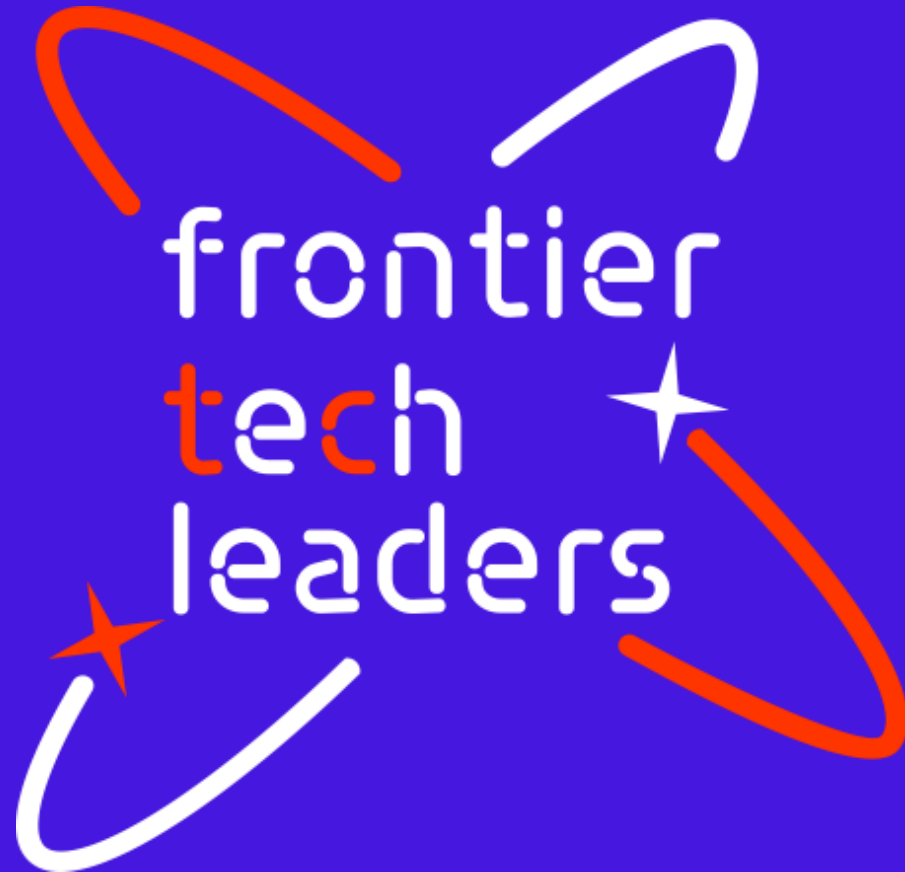
Table 1 qc1Ncs_MODELs evaluation metrics

	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)
del															
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 Refinement and Testing

- Overview of the refinement phase
- Techniques used for model improvement
- Overview of the test submission phase
- Metrics and results on the test dataset





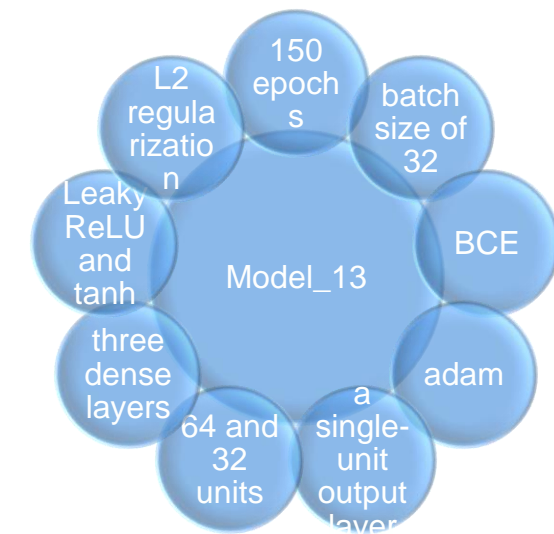
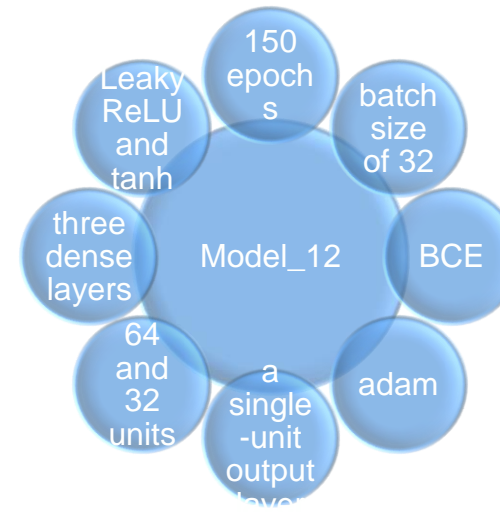
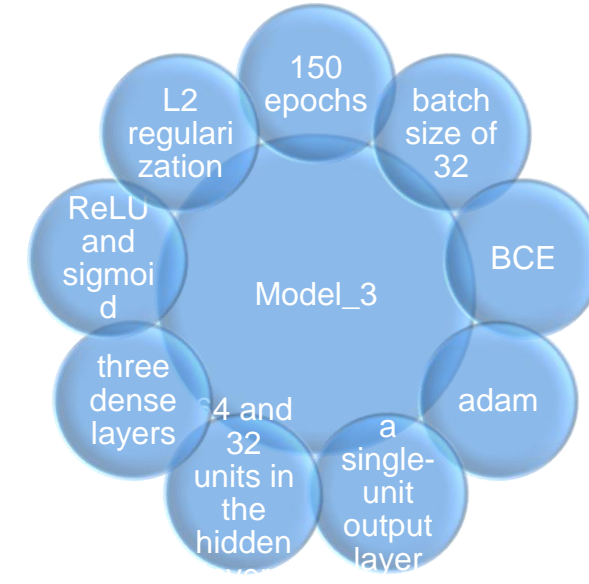
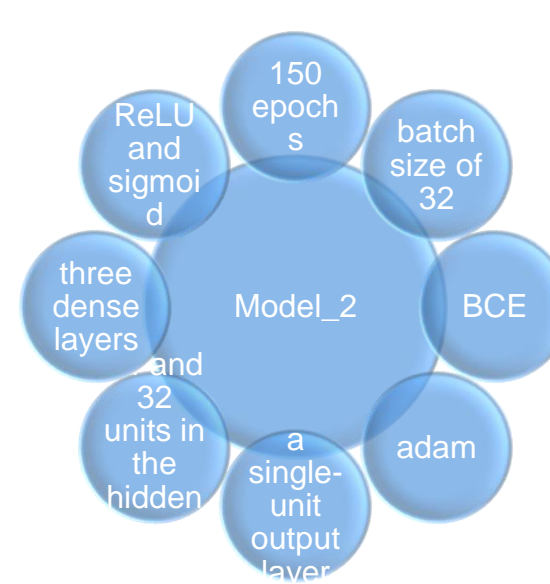
Result



Evaluation Results

Accuracy (testing)

- qc1Ncs_MODELS: Model_13=84.72%
- CPR_CRR_MODELS: Model_2 =87.5%
- (N1)60cs_MODELS: Model_2=82.19%
- SPT_CRR_MODELS: Model_12=75.14%
- Vs_MODELS : Model_13=69.81%
- Vs_MODELS: Model_13=72.64%
- CRR_MODELS: Model_3=72%





Deployment



Deployment

- Overview of the deployment phase
- Model serialization, serving, and API integration

Liquefaction Prediction

Predict liquefaction based on input parameters.

z(m)

dw(m)

svo(kPa)

s'vo(kPa)

Mw

amax(g)

qc1Ncs

Clear

Submit

Prediction

Flag

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!

