**CANVA LINK FOR PRESENTATION:** <https://www.canva.com/design/DAF9ysIBWbE/GJv4kgu3O2fTyQXHWqzVcQ/edit?utm_content=DAF9ysIBWbE&utm_campaign=designshare&utm_medium=link2&utm_source=sharebutton>

***CANVA LINK OF POSTER: 1920x1080***

<https://www.canva.com/design/DAF939ADqGw/wfiZ-40QqlQWj3VPGiQL3w/edit?utm_content=DAF939ADqGw&utm_campaign=designshare&utm_medium=link2&utm_source=sharebutton>

***CANVA LINK OF POSTER2 : 1080 x 1080***

<https://www.canva.com/design/DAF93z8iVno/OhZdajxvEV2sKELhxX1xPw/edit?utm_content=DAF93z8iVno&utm_campaign=designshare&utm_medium=link2&utm_source=sharebutton>

**TECHNICAL REPORT**

**Abstract**

**Introduction**

*Background*

The Philippines has a well-documented history of liquefaction-induced disasters. The 1990 Luzon earthquake, for example, triggered extensive liquefaction in Dagupan City, causing severe damage to buildings and displacing thousands. Similar events have occurred in Davao del Sur and other regions, highlighting the vulnerability of the Philippines to this earthquake-related hazard.

However, current methods for assessing liquefaction potential often lack the predictive accuracy and resolution needed for effective mitigation strategies. Traditional analytical methods rely on simplified assumptions and standardized protocols, which may not capture the unique geological and seismic characteristics of specific locations. The resulting risk assessments may be overly conservative or underestimate the true liquefaction threat, leading to inefficient resource allocation and potentially leaving vulnerable areas exposed. A case in point is the soil liquefaction that occurred in 1989, Loma Prieta, California.

The most widely used method for liquefaction assessment was proposed by Idriss and Boulanger (2014) in their paper *“SPT-Based Liquefaction Triggering Procedure”.* This approach utilizes case studies and laboratory analysis of frozen soil samples to derive relationships between induced stress and soil properties. The method presents itself as an empirical approach that is supported by theoretical knowledge and lab testing, however, despite those efforts there are still cases where this method falls short of its results.

Developing a more accurate and interpretable model for predicting soil liquefaction holds the potential to significantly improve disaster risk reduction strategies in the Philippines. By providing a deeper understanding of factors that trigger soil liquefaction and provide insights on how it can be mitigated, this model can help safeguard lives, infrastructure, and economic well-being in the face of a recurring seismic threat.

*Problem Statement*

Given the current available methods of assessing soil liquefaction and its performance and the fact that in earthquake-prone areas like the Philippines, assessing soil liquefaction remains critical, ***can we develop a machine learning model that can both predict and help mitigate soil liquefaction?***

*Objectives*

The objectives of this study are as follows:

1. **Develop an accurate and explainable model**
   * Predict, with a higher accuracy than the empirical approach, if a site will trigger soil liquefaction given the earthquake parameters.
   * Interpret the model, and explain the basis of its predictions.
2. **Utilize counterfactual analysis**
   * Provide suggestions on the optimal modifications of the soil’s properties that could mitigate soil liquefaction.

**Dataset**

The dataset utilized for the study is extracted from Idriss and Boulanger’s study regarding SPT-Based Liquefaction Triggering Procedures. It contains an accumulated history of SPT-based liquefaction cases, holding 254 data points and 27 features. Below are the features of the final dataset used and subjected to the Machine Learning models discussed in the succeeding sections:

| **Feature** | **Description** |
| --- | --- |
| Location | Geographic location or identifier of the seismic measurement station. |
| M | Magnitude of the earthquake on the Richter scale. |
| a | Peak ground acceleration recorded during the earthquake. |
| LIQ | Binary indicator (Yes/No) if liquefaction was present. |
| Avg Depth | Average depth of soil layers at the seismic station, typically in feet. |
| GWT Depth | Depth of the groundwater table at the location, typically in feet. |
| Total Vertical Stress | The total vertical stress on the soil at the seismic station. |
| Effective Vertical Stress | The effective vertical stress that contributes to soil strength. |
| Avg N | Average standard penetration test (SPT) blow counts. |
| N1-60 | Standard penetration test blow counts, normalized to a 60% hammer efficiency. |
| Cb | Correction factor for borehole diameter in SPT. |
| Ce | Correction factor for hammer energy ratio in SPT. |
| Cn | Correction factor for effective overburden pressure in SPT. |
| Cr | Correction factor for rod length in SPT. |
| Cs | Correction factor for sampler type in SPT. |
| FC% | Fine content percentage, proportion of fine particles in the soil. |
| N1-60-cs | Corrected SPT N-value for overburden and hammer energy efficiency. |
| α | Coefficient used in calculations for seismic soil response. |
| β | Coefficient used in calculations for seismic soil response. |
| rd | Shear stress reduction coefficient for depth. |
| K\_sigma | Coefficient reflecting the effect of confining stress on soil stiffness. |
| MSF | Magnitude scaling factor, used to adjust CSR for earthquakes of different magnitudes. |
| CSR | Cyclic stress ratio, indicating the stress on soil during seismic shaking. |
| CSR norm | Normalized cyclic stress ratio. |
| CRR | Cyclic resistance ratio, a measure of the soil's resistance to liquefaction. |
| Assessment | Qualitative assessment of liquefaction potential or other seismic considerations. |
| Data Source | Reference to the origin or source of the data. |

(Will place this as Markdown or Picture, and description is subject to change.)

IF (1) WAS CHOSE: Not all features were utilized, and feature engineering was executed which will all be discussed in the next section: Methodology.

Two datasets will be utilized: (1) the dataset to be subjected to the seven Machine Learning model with the target variable as `’LIQ’`, and (2) the dataset containing only the predicted values of the Empirical Method under the feature `’Assessment’`, and the actual values of the case history under `’LIQ’`.

**Methodology**

[PICTURE]:

1. Data Extraction
2. Data Loading
3. Data Preprocessing
4. Exploratory Data Analysis
5. Feature Selection and Feature Engineering
6. Subjecting the Final Dataset to Seven Machine Learning Models
   1. Initial Train-Test Split
   2. Pipeline and GridSearchCV
7. Select Best Model and Provide Parameters to Beat Mean Score of Empirical Method
   1. Train-Test Scenario on 30 splits
   2. Each scenario, GridSearch will be performed, then accuracy score of both XGB and Empirical Method will be obtained
   3. After all scenarios, average the scores of XGB and Empirical Method
   4. Verify reliability of scores using P-value. Present Standard Deviation
8. Interpret the Model using SHAPLEY
9. Execute Counterfactual Analysis to Help Mitigate Soil Liquefaction

*Data Extraction*

The dataset utilized for this project is extracted from Idriss and Boulanger’s study regarding SPT-Based Liquefaction Triggering Procedures. It contains an accumulated history of SPT-based liquefaction cases, holding 254 data points and 27 features.

*Data Loading*

The dataset, in the form of an Excel file (.xslx) was loaded into a dataframe using Pandas.This provides us all features regarding soil properties, earthquake scenarios, and liquefaction observations.

*Data Preprocessing*

```target = 'LIQ'

df['LIQ'] = df['LIQ'].map({'Yes': 1, 'No': 0, 'Mar-ginal': 0})

df['Assessment'] = df['Assessment'].map({'Yes': 1, 'No': 0})

empirical\_df = df.loc[:,['LIQ','Assessment']]

```

The two dataframes are prepared: (1) the dataframe to be subjected to the seven Machine Learning model with the target variable as `’LIQ’`, and (2) the dataframe containing only the predicted values of the Empirical Method under the feature `’Assessment’`, and the actual values of the case history under `’LIQ’`.

*Exploratory Data Analysis*

This section checks for class imbalances and distributions of each of the features used in the study.

*Feature Selection and Feature Engineering*

*(Porewater Pressure na to, tapos di na ginamit si Stress Ratio and a\*MSF)*

```df['Stress Diff'] = df['Total Vertical Stress'] - df['Effective Vertical Stress']

df['TotalEffectiveRatio'] = df['Total Vertical Stress'] / df['Effective Vertical Stress']

df['a\*MSF'] = df['a'] \* df['MSF']```

Features were selected based on two criteria:

1. Features must be significant to the Machine Learning model, ultimately contributing to the increase of accuracy of predicting whether the soil of the location is liquefiable.
2. Features must be factors that are easily understood and can be easily utilized in counterfactuals.

In order to obtain features that meet the criteria, the selection was executed in an iterative manner, running a combination of features to the seven Machine Learning models to achieve an accuracy score above 80%.

Below are the final features subjected to the seven Machine Learning models.

<TABLE WITH FEATURE AND DESCRIPTION>

The dataset is initially split into Train-Test, having 10% of the whole dataset as the Test set. The 90% Training and 10% Testing split will be consistently implemented throughout the implementation of the model. (indicate cv splits)

*Subjecting the Final Dataset to Eight Machine Learning Models*

Seven known classifiers were tested in an iterative manner with the previous section, namely:

1. k-Nearest Neighbours Classifier
2. Naive-Bayes Classifier
3. Logistic Regression (with L1 Regularization, with L2 Regularization)
4. Support Vector Classifier
5. Decision-Trees Classifier
6. Random Forest Classifier
7. Gradient Boosting Method
8. XGBoost

In order to ensure reliability of the results when selecting the Machine Learning model, an `accuracy` scoring was used along with averaging the overall score of the GridSearch per Machine Learning model.

\*\*Below are the results of the Machine Learning models, and with the mean test score of 86.8%, the XGBoost Classifier will be the chosen Machine Learning model to be tuned.

*Select Best Model and Provide Parameters to Beat Mean Score of Empirical Method*

With the best Machine Learning model presented, this section aims to beat the Empirical Method’s mean score. This is done by testing 30 Train-Test splits, indicating 30 random scenarios. For each scenario, the accuracy score of the Machine Learning model is obtained. Similarly, the accuracy score of the Empirical Method is obtained. After obtaining all results throughout the 30 scenarios, the Train-Test mean accuracy score for the Machine Learning Model is obtained. Mean accuracy score of the Empirical Method is obtained as well. Finally, the Machine Learning model’s mean test accuracy score is compared to the Empirical Method’s.

To mitigate the anticipated limitations of the dataset, a t-test was conducted to verify the statistical significance and validity of the results. This approach also addresses the potential issue of overfitting, considering that the machine learning model underwent testing across 30 Train-Test scenarios.

**Discussion and Results**

The model achieved a mean score of 84.69% which is 1.69% higher than the mean score of the empirical model. The Standard Deviation of the accuracy score is 7.48% for the Machine Learning model, and 7.38% for the Empirical Method.

To move forward to the Interpretability and Counterfactual Analysis, GridSearch was performed on one train-test split to attain the final model.

*SHAP* – Global Interpretability

Using SHAP enables researchers and stakeholders to understand how the Machine Learning model works throughout its development with the training and testing datasets. For this study, the top predictors are `‘N1-60’`, `’M’`, `’a’`, and `’FC%’`.

| **Feature** | **Description** |
| --- | --- |
| N1-60 | Standard penetration test blow counts, normalized to a 60% hammer efficiency. |
| M | Magnitude of the earthquake on the Richter scale. |
| a | Peak ground acceleration recorded during the earthquake. |
| FC% | Fine content percentage, proportion of fine particles in the soil. |

[BEESWARM PLOT]

According to the Beeswarm plot generated, the higher the `’N1-60’`, the lower the probability of the soil liquefying. This is because `’N1-60’` dictates the soil's density and stiffness. The variables `’M’` and `’a’`, referring to the ground shaking intensity, suggest that lower values mean a lower probability for the soil to liquefy. Finally,`’FC%’`, which refers to the amount of silts and clays in the soil, indicates that soil with more silts and clays is more resistant to liquefaction.

In conclusion, the application of SHAP for global interpretability in this study has provided significant insights into the factors influencing soil liquefaction risk. By analyzing features such as `’N1-60’`, `’M’`, `’a’`, and `’FC%’`, researchers and stakeholders can gain a deeper understanding of the complex interplay between soil properties and seismic activity on liquefaction potential. This enhanced interpretability not only aids in the accurate assessment of liquefaction risks but also supports the development of more effective mitigation strategies, ultimately contributing to the safety and resilience of infrastructure in earthquake-prone areas.

*SHAP* – Instance-level Probability

To refine the understanding of the model's predictions, the subsequent section will employ SHAP's instance-level interpretability along with DICE counterfactual analysis. Analyzing a location known for its liquefiable soil would add greater value to this case study. Therefore, 'McKim Ranch A,' an area with liquefiable soil, will be examined.

*Case Scenario: McKim Ranch A*

[BEESWARM PLOT]

Reading the waterfall plot from bottom to top, the Machine Learning model was initially inclined to predict that the soil would not liquefy. However, because both `'a'` and `'N1-60'` had high values, this was sufficient to entirely shift the prediction towards the soil being liquefiable.

Following the intuition of the model to arrive at its prediction, it enables the stakeholders to see which factors can be influenced and whether it is feasible to mitigate soil liquefaction risks. This is where DICE comes into play, offering a strategic approach to exploring and addressing these factors.

*DICE* – Prescriptive Analytics

DiCE (Diverse Counterfactual Explanations) was introduced by Microsoft in 2018, and its ultimate purpose is to show how slight modifications to input features could lead to different outcomes from the Machine Learning model, thereby offering a form of "what-if" analysis to understand and possibly alter the decision made by an ML model​. This tool adds great significant value to geotechnical engineering as it proposes solutions on how to mitigate risks in soil studies.

In the application of DiCE (Diverse Counterfactual Explanations) to the case of McKim Ranch A, the focus is placed solely on adjusting the N1-60 value. This targeted approach suggests that, among the various factors that could be modified to improve soil conditions or meet specific project requirements, the N1-60 value holds the most significant leverage.

By proposing an increase in the N1-60 value from 4.6 to 14.4, DiCE indicates a strategic direction for soil stabilization efforts, emphasizing that other variables may remain unchanged.

By concentrating resources and efforts on enhancing the N1-60 value, stakeholders can achieve desired outcomes efficiently, without the need for broader alterations to the site's geotechnical profile.

**Conclusion**

This study successfully developed a machine learning model using XGBoost to predict soil liquefaction probability, achieving a mean accuracy of 84.69%. This surpasses the mean accuracy of the established empirical method (83%) by 1.69%, demonstrating the potential of XGBoost for improved liquefaction prediction.

The interpretability analysis using SHAP provided valuable insights into the key factors influencing the model's predictions. Features like N1-60 (soil density), earthquake magnitude (M), peak ground acceleration (a), and fine content percentage (FC%) were identified as significant contributors to liquefaction risk. This understanding empowers stakeholders and researchers to make informed decisions regarding risk assessment and mitigation strategies.

Furthermore, the application of DICE counterfactual analysis allowed for exploring "what-if" scenarios and identifying actionable steps to mitigate liquefaction risks. In the case of McKim Ranch A, increasing the N1-60 value emerged as a strategic recommendation, potentially achieved through soil densification techniques. This targeted approach facilitates efficient resource allocation and minimizes unnecessary alterations to the site's geotechnical profile.

In conclusion, this study demonstrates the effectiveness of XGBoost in predicting soil liquefaction probability, surpassing the accuracy of the conventional empirical method. The interpretability and counterfactual analysis capabilities further enhance the model's value by providing valuable insights for informed decision-making and targeted mitigation strategies. By integrating these findings into future practices, stakeholders can significantly contribute to safeguarding lives, infrastructure, and economic well-being in earthquake-prone regions like the Philippines.

**Recommendations**

In light of the discoveries made in the research, specifically with the success of developing the Machine Learning model, and the use of SHAP and DiCE for interpretability, the researchers have recommendations to further refine and enhance soil liquefaction prediction built from this study.

1. **Incorporation of Additional Data:** Expanding the training dataset with more data can help the model attain generalization. Data from more countries can provide a diverse set of unique soil composition and properties that can help refine the model. Including more data from the Philippines itself can help capture the varieties of soil conditions all over the country making the model more robust when used on Philippine soils.
2. **Integration with Geographic Information Systems (GIS):** Developing a user-friendly platform that integrates the XGBoost model with GIS capabilities would allow stakeholders to easily assess liquefaction risks across specific locations within the Philippines, facilitating informed decision-making at the regional and national levels.
3. **Cost-Sensitive Analysis:** Integrating cost considerations into the model development and evaluation process is something that can be explored
   1. **Gathering historical data on past liquefaction events and their associated economic losses.** This data would help estimate the potential costs of false negatives (failing to predict liquefaction that occurs).
   2. **Collecting information on the costs associated with implementing various soil improvement techniques.** This data would help assess the potential financial burden of false positives (predicting liquefaction that doesn't occur, leading to unnecessary mitigation efforts).

By pursuing these research directions, stakeholders in the Philippines can gain a deeper understanding of soil liquefaction susceptibility and implement more effective mitigation strategies, ultimately fostering a safer and more resilient future for the nation.

**References**

Cetin, K. O., Seed, R. B., Kayen, R. E., Moss, R. E., Bilge, H. T., Ilgac, M., & Chowdhury, K. (2018). Dataset on SPT-based seismic soil liquefaction. *Data in brief*, *20*, 544-548. <https://www.sciencedirect.com/science/article/pii/S2352340918308953?via%3Dihub>