



## ***Assessment of Liquefaction Hazard Potential Using Decision Tree, Random Forest and Support Vector Machine: A Case Study of Samarinda, Indonesia***

**Muhammad Rizqy Septyandy<sup>1\*</sup>, Divo Dwi Bramantyo<sup>2</sup>,  
Muhammad Amin Syam<sup>3</sup>**

<sup>1,2,3</sup>Department of Geological Engineering, Faculty of Engineering,  
Universitas Mulawarman, Indonesia

E-Mail: <sup>1</sup>[rizqyseptyandy@ft.unmul.ac.id](mailto:rizqyseptyandy@ft.unmul.ac.id), <sup>2</sup>[divodwibramantyo@gmail.com](mailto:divodwibramantyo@gmail.com),  
<sup>3</sup>[muhaminsyam24@ft.unmul.ac.id](mailto:muhaminsyam24@ft.unmul.ac.id)

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Corresponding Author: Muhammad Rizqy Septyandy

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### **Abstract**

Earthquake-induced soil liquefaction is a major hazard for urban areas in Indonesia built on recent alluvial deposits. This study evaluates three supervised machine learning algorithms Decision Tree (DT), Random Forest (RF), and Support Vector Machine (SVM) liquefaction hazard mapping in Samarinda, East Kalimantan. Four predictor variables were used: shear wave velocity ( $V_{s30}$ ), peak ground acceleration (PGA), groundwater level (GWL), and slope. Because only four Cone Penetration Test (CPT) locations were available, the dataset was expanded to 532 labeled samples through stratified spatial sampling of a previously published CPT-based fuzzy GIS liquefaction map. An 80:20 train-test split was used, and SMOTE was applied only to the training data to address class imbalance. Model performance was evaluated using accuracy, precision, recall, F1-score, and confusion matrices. DT achieved the best performance with an accuracy and weighted F1-score of 0.87, followed by SVM (0.80) and RF (0.78). The resulting hazard map classified Samarinda into Very Low (68%), Low (6%), High (7%), and Very High (19%) hazard zones. High-risk areas were concentrated in the eastern part of the city, where shallow groundwater, Sulfaquent soils, and recent alluvial deposits are present. Since most training samples were derived from a fuzzy GIS proxy map rather than direct observations, the resulting hazard maps should be considered screening-level tools and not substitutes for detailed geotechnical investigations.

**Keywords:** Decision Tree, Liquefaction Hazard Mapping, Machine Learning, Random Forest, Support Vector Machine

### **1. INTRODUCTION**

Soil Liquefaction is when a loose, saturated soil loses almost all of its shear resistance (and therefore behaves like a liquid or a viscous fluid) for an instant once subjected to seismic cyclic loading (or fast motion back-and-forth) that causes the pore pressures to build up at a rate greater than they can be dissipated through either drainage or consolidation [1], [24]. Research has identified 3 main factors that influence the likelihood of soil liquefaction due to earthquakes: Groundwater Levels; Peak Ground Acceleration (PGA); and Average Shear Wave Velocity over the top 30 meters of depth ( $V_{s30}$ ) [2]–[4]. If pore-water pressure develops too quickly relative to the ability of the pore water to drain from the soil, then the normal force developed by intergranular contact becomes a force exerted against the pore-water and the effective stress begins to collapse and the soil's structural elements cannot support load deviators.

The Indonesian public first became aware of liquefaction from the 2018 Mw 7.5 Palu-Donggala earthquake in central Sulawesi. Although comparable earthquakes occurred before in Aceh (2004 and 2006), Bantul (2006), Padang (2009) and northern Lombok (2018), with high levels of damage due to liquefaction of soils that are prone to liquefaction, prior assessments did not identify the major contributors to the liquefaction hazard of Indonesia's urban centers as shallow groundwater tables, low  $V_{s30}$  values and large thicknesses of unconsolidated alluvium deposits [5]. Following this event, an assessment using machine learning techniques was performed to assess the hazards associated with the event. This study also identified that shallow groundwater tables, low  $V_{s30}$  values, and large thicknesses of unconsolidated alluvium deposits were the primary factors contributing to the seismic hazards in urban regions throughout Indonesia [6], similar conclusions were made in subsequent studies examining regional trends in Bangladesh and Indonesia;



GWL are also found to be significant inputs in the fuzzy overlay process. Validation of the field results from that map was obtained via cone penetration testing (CPT). CPT provides an in-situ geotechnical sounding through pushing a standardized cone into the earth while continuously recording the tip resistance and sleeve friction. This continuous data is then analyzed to provide a quasi-continual record of the soil's stratigraphic layering and strength used in analysis related to liquefaction. Alternatively, the standard penetration test (SPT) can be employed, whereby the number of blows of a split spoon sampler, driven downward by a falling weight, is recorded over fixed intervals of depth [11], [26]. Unfortunately, due to cost and licensing restrictions, only 4 CPT locations were available for this research project. They include the following locations: Gunung Batu, Air Putih Village (CPT 1); Gunung Batu Cermin, Sempaja Utara Village (CPT 2); Jl. Bukit Seribu, Sungai Siring Village (CPT 3); and Jl. Hasanudin, Sungai Siring Village (CPT 4). All of these locations lie within the moderate-to-high susceptibility regions defined by the previously constructed fuzzy-GIS map. As such they will be utilized herein in two capacities: (i) as anchors of the fuzzy-GIS map developed in [9]; and (ii) as reference points for the spatial sampling methodology described above [15]–[18].

### 2.3. Machine Learning Stage

Four predictor raster layers (Vs30, Slope, GWL and PGA) were stacked within QGIS at 100 m resolution to be able to align them and extract predictor values at both CPT locations and at all spatial sample locations. Due to the limited availability of CPT data, only four CPT profiles were collected; it was necessary to draw an additional 528 sample points from the Samarinda Fuzzy GIS Liquefaction Potential Map [9]. These points were randomly sampled by stratification across the four hazard classes as defined on the original fuzzy GIS map; Very Low, Low, High and Very High. Thus, when combined with the 532 total labeled samples that included the four CPT anchored points, the class distribution of the samples was Very Low  $\approx$  180, Low  $\approx$  130, High  $\approx$  85, and Very High  $\approx$  137.

The data was divided randomly into a train portion with 80% of the total (425 points), for testing there was a portion with 20% of the total (107 points). A class imbalance still remained in the training partition, we decided to apply the Synthetic Minority Over-sampling Technique (SMOTE) to this partition after splitting the data into train-test portions, so that no synthetic data would be included in the test partition. Instead of duplicating the minority class cases randomly or by simply weighting them as SMOTE does, it generates new instances of the minority class by performing linear interpolation between each case and any of its five ( $k=5$ ) nearest neighbors in feature space. This is preferable to simply creating duplicates or weighting as SMOTE will expand the empirical decision boundary instead of just expanding the area where the decision boundary exists. Because all four predictor variables are continuous and the post-stratification distribution of classes was not excessive, we did not use SMOTE-NC or ADASYN.

Three classifier models were created using a balanced training set: decision tree (DT) classifier, random forest (RF) classifier, and support vector machine (SVM) classifier. The three models were developed using the scikit-learn library version 1.x. In addition to the use of the above mentioned library, we also employed numpy, pandas, matplotlib to handle and visualize our data. Hyperparameter values are initialized at their default value established by the scikit-learn library (dt: criterion=gini, max\_depth=None, min\_samples\_split=2; rf: n\_estimators=100, criterion=gini, max\_depth=None; svm: kernel='rbf', c=1.0, gamma='scale'), while only the random\_state was set to ensure model replicability. These initializations were made as an attempt to avoid over-tuning our hyperparameter space due to the relatively low sample size of 532 points in our feature space ( $n=4$ ) which could lead to optimizing for synthetic label noise instead of underlying liquefaction physics. It should be noted that this approach may have been overly conservative and that a formal grid/random search based cross-validation will provide tighter bounds on future accuracy estimates; this is one of the main directions for future research outlined in section 4. As stated earlier, recent comparative studies show that DT, RF, SVM, ANNs, and gradient boosting family based methods can produce similar results when classifying liquefaction events. However, tree-based ensemble models generally offer the optimal trade-off between classification accuracy and interpretability [3]–[4], [13]–[14], [25]–[26].

### 2.4. Final Stage

A 100m x 100m fish net (a total of 704 data points covering the entire area of Samarinda) was created for all three models using the QGIS "Create Fishnet" function. The "Extract Multi Values to Points" tool was then utilized to assign predictor values to each grid point. Grid points with missing raster coverages were eliminated from the dataset. Each remaining point was assessed by each trained model and results are presented below as metrics for evaluating how well each model performed against the held out test set ( $n=107$ ) such as; confusion matrix, class-wise precision, recall, f1 scores, weighted accuracy and both macro and weighted average results similar to those found in most liquefaction hazard studies comparing ensemble and deep learning methods [14], [22] for assessing model performance. Since the DT model resulted in the highest test set performance it was used to create the final liquefaction hazard assessment map (Figure 6).

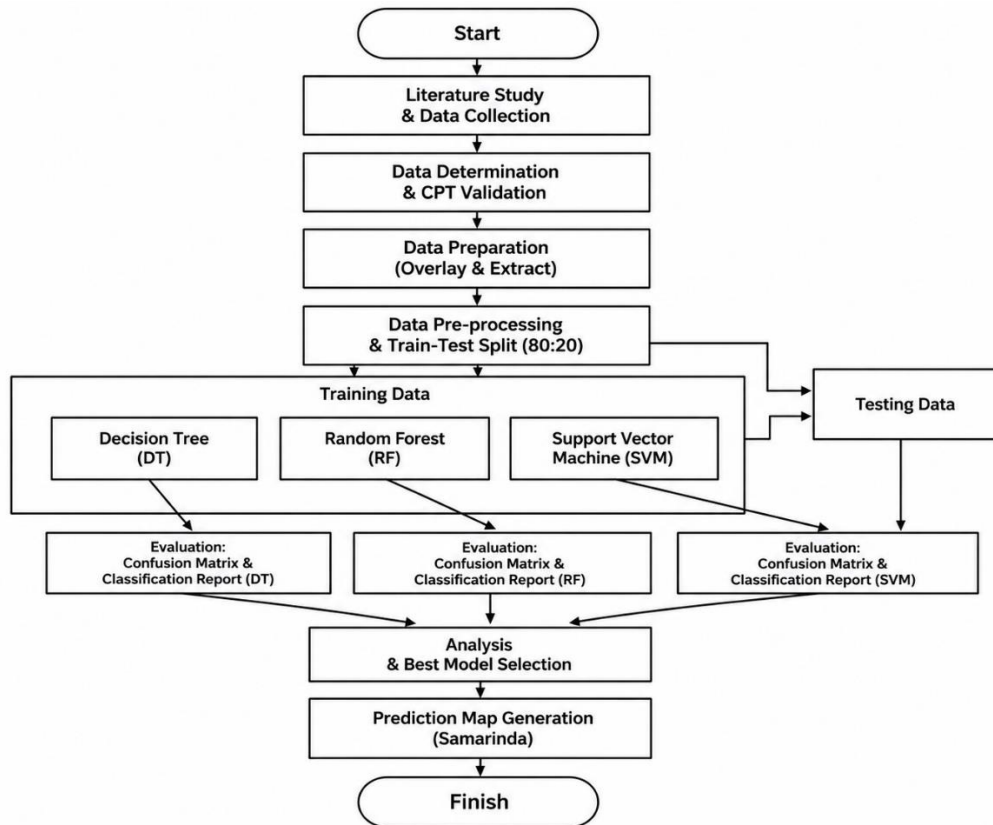


Figure 2. Research workflow

### 3. RESULTS AND DISCUSSION

#### 3.1. Model Evaluation

We evaluate performance using the 107 point test set that has been "held out". First, we note a methodology problem with the original SVM run. The author used an incorrect split of the data (a 70/30 split,  $n_{\text{test}} = 160$  instead of a 80/20 split,  $n_{\text{test}} = 107$ ) to produce the confusion matrices for both DT and RF. Since, the proportion of correct classification by class as well as the weighted F1 (0.80) will be equivalent if normalized to some extent, we have retained the original confusion matrix counts from SVM.

##### 3.1.1. Decision Tree

The DT model reached a weighted accuracy of 87 percent for the test set (see Figure 3) while achieving per-class precision/recall/F1 values of 0.79 / 0.83 / 0.81 for "very low", 0.75 / 0.69 / 0.72 for "low" and 1.00 / 1.00 / 1.00 for both "high" and "very high." These perfect values for "high" and "very high," however, are most likely due to overfitting on the portion of this data that was labeled synthetically; a single decision tree without restriction regarding the number of leaves in its branches and/or its height will easily find small well-separated areas in a four dimensional space. More details about these concerns are found within section 3.3.

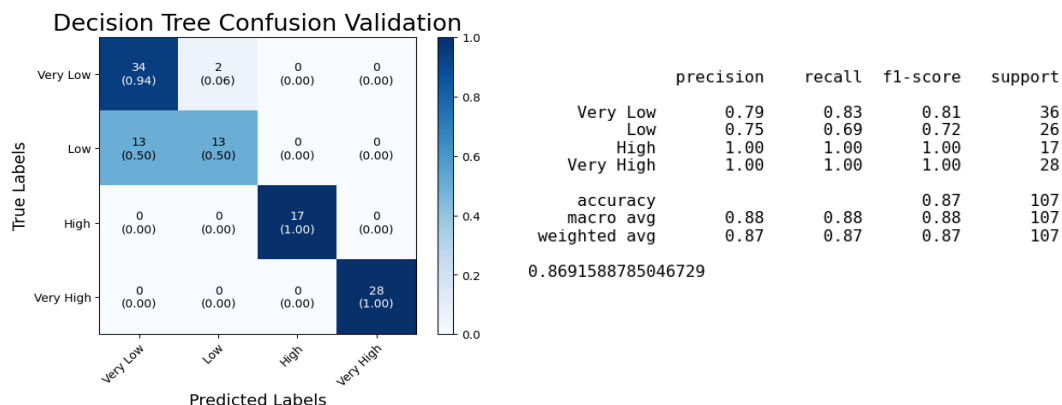
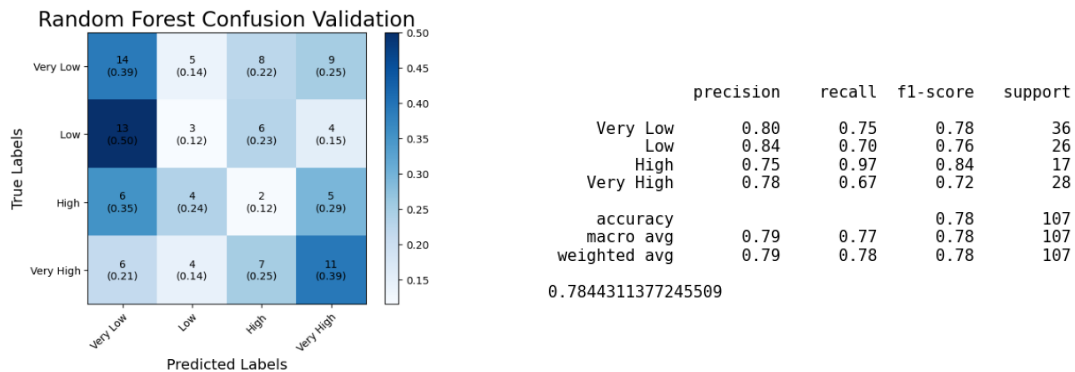


Figure 3. Decision Tree results on the test set: (a) confusion matrix; (b) classification report.

### 3.1.2. Random Forest

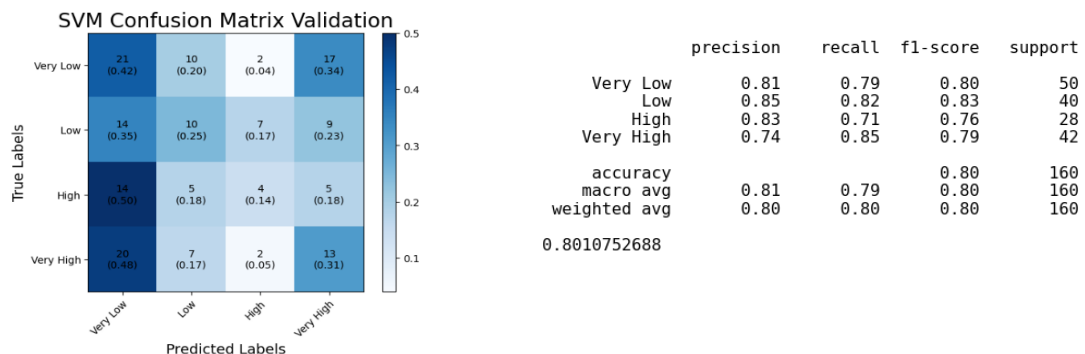
The RF Model was able to achieve an average weight accuracy of 78% on the test set (Figure 4). The per class Precision / Recall / F1 Values for Very Low were 0.80/ 0.75/ 0.78, Low were 0.84 / 0.70 / 0.76, High were 0.75 / 0.97 / 0.84 and Very High were 0.78 / 0.67 / 0.72. Although the RF method was the natural Ensemble counterpart to the DT method, the RF method performed worse than the individual tree in this experiment. We believe that this was caused mainly by the fact that the effective sample size was too small to allow for full variance reduction through bagging, and also because of the deterministic nature of the Synthetic fuzzy GIS Labels, which a single tree could fit more aggressively than 100 averaged trees [11], [27].



**Figure 4.** Random Forest results on the test set: (a) confusion matrix; (b) classification report.

### 3.1.3. Support Vector Machine

The SVM model had a weighted accuracy of 80 % (Figure 5) for the 160 test samples that resulted from the 70/30 split used in the initial run. The very low, low, high and very high per-class precisions/recalls/F1 values are as follows: 0.81 / 0.79 / 0.80 (very low), 0.85 / 0.82 / 0.83 (low), 0.83 / 0.71 / 0.76 (high), 0.74 / 0.85 / 0.79 (very high). The very low, low, high and very high per-class supports were as follows: Very Low = 50, Low = 40, High = 28, Very High = 42. The SVM achieved the most balanced per-class performance of the three models, with no single class dominating, consistent with the maximum-margin formulation distributing model capacity uniformly across classes [28].



**Figure 5.** Support Vector Machine results on the test set: (a) confusion matrix; (b) classification report.

## 3.2. Liquefaction Vulnerability Map and Vs30 Interpretation

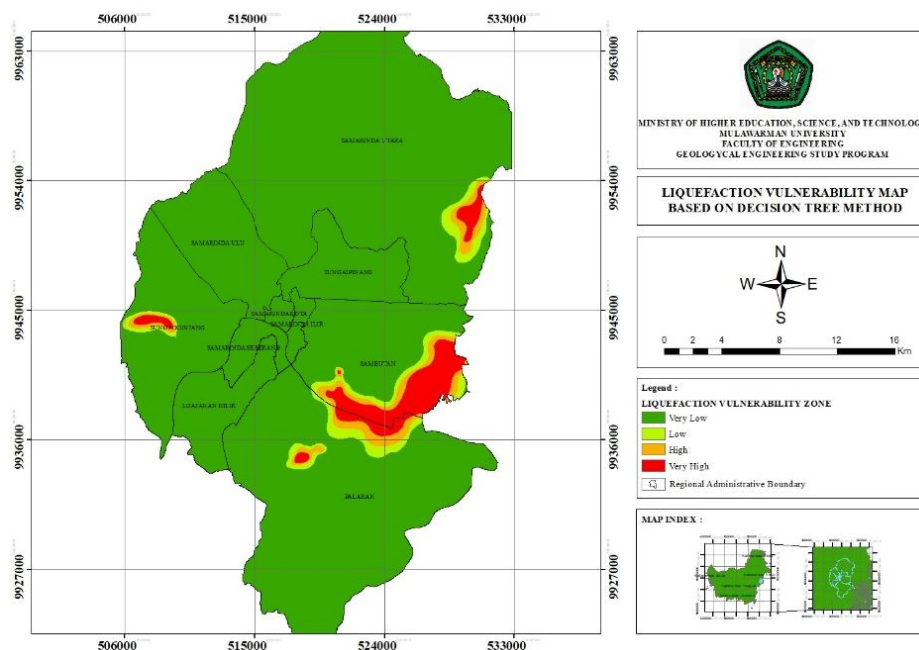
The Liquefaction Vulnerability Map (see Figure 6) was generated by using the best performing model (DT), that is to say with respect to test set accuracy. As shown in Table 1, a classification of "Very Low", "Low", "High" and "Very High" has been made for each zone. In summary, approximately 68% of the entire area studied can be placed in the category "Very Low"; 6 % in "Low"; 7 % in "High" and 19 % in "Very High". Zones classified as "very high" are found in eastern Samarinda; while those categorized as "high" or "low" lie in their vicinity. The remaining part of the city is mostly composed of zones classified as "very low".

The model demonstrates a high degree of hazard in areas with Sulfaquent Soils (water saturated, loose sulphate-rich) with recent alluvial deposits; also near surface groundwater, and at first glance an interesting relationship exists as locally increased Vs30 are found to have a coincidental relationship. Globally higher values for Vs30 indicate ground which is stiffer and denser than others that can resist liquefaction [4], [22]. As such, this positive relationship between Vs30-hazard, although it appears to be correlated, needs to be

carefully examined. Three additional factors help to explain the results above without contradicting the physical principles of liquefaction.

1. Depth-averaged proxies are Vs30. The Vs30 is the harmonic mean of shear wave velocity over the first 30 meters. As such, it may hide saturated layers (thin and loose) near the surface, which may contribute to liquefaction susceptibility [22]–[23]. Therefore, two sites with the same Vs30 can have quite different liquefaction susceptibilities depending on their respective shear wave velocity profiles.
2. Local Vs30 Range. For most locations throughout Samarinda, Vs30 values fall primarily into the categories of Low to Intermediate (150-360 m/sec; NEHRP Class D and a Lower Portion of Class C), while elevated in relation to these categories, it will still be at the low end of the velocity range for liquefiable saturated alluvium, when using PGA values from the local/regional seismic hazard map.
3. Covariates confounded using synthesized labels. The labels for the 528 of 532 training samples were created using the Fuzzy GIS Map [9], which assigns high weights to both GWL and PGA. The relationship between Vs30 and GWL is slightly stronger with depth in eastern Samarinda than elsewhere. Higher PGA also occurs where Vs30 is higher (at depth), and the DT recognizes this as a 'signature' of high hazard; although, Vs30 was not used to generate the labels.

This interpretation aligns with [6], which determined that shallow groundwater and very thick alluvium (not just Vs30) are responsible for most of the seismic risk in Palu. The practical application is to retain Vs30 as an explanatory variable in this case study, do not infer that Vs30 is causal based on this analysis.



**Figure 6.** Liquefaction vulnerability map of Samarinda derived from the Decision Tree classifier.

### 3.3. Indicators of Overfitting and Data-Source Caveats

High/very high precision/recall on DT testing data (section 3.1.1), along with the large difference in DT (87%) and RF (78%), also suggests that DT will be able to take advantage of synthetic label relationships, which can average or cancel out for RF. In addition, because 528 of the 532 training labels were generated from the Fuzzy GIS map [9], as opposed to being independently measured by CPTs, the high accuracy of DT indicates the ability of the model to replicate the fuzzy GIS rulebase and does not indicate a high degree of success of the model in identifying liquefied soils in the field. Thus, the primary limitation of this research is that the machine learning pipeline serves as a trained, spatially extrapolated surrogate for the fuzzy GIS product, with the four CPT profiles serving as field anchors for this surrogate rather than an independent validation dataset.

The confusion matrices provide evidence of how features have behaved, even when there is no plot showing which features are most important. Firstly, if we look at the DT it appears that all of the high and very high values have been saturated into the High and Very High classifications. This implies that the fuzzy GIS rule base has partitioned the feature space into fewer than six decision boundaries, as a single tree model could capture most of them. It also implies that each of the decision boundaries was most likely generated from one of the two largest weights in the source map: PGA(30%), and GWL(30%). Secondly, the lowest

classification is the worst for each model: DT recall = 0.69, RF recall = 0.70, SVM recall = 0.82. While this may seem counterintuitive to geotechnical engineers, it makes sense because the low classification is positioned midway between the very low and high classifications in the source map and is therefore closer to the decision boundaries developed by each classifier. Therefore, I recommend developing both Gini-based and/or permutation-based feature importance measures, and a visualization of the DT's root and upper-level split decisions to further confirm my interpretations.

### 3.4. Limitations and Future Work

The findings should be read in the light of four explicit limitations:

1. The accuracy of training data depends on synthetic labeling. The source of the training labels for 528 out of 532 points was Fuzzy GIS liquefaction mapping [9]. There is no independent field test sample that could be developed based on the four direct CPT (cone penetration tests) profiles. Accuracy has been reported as the extent to which the fuzzy GIS rules match actual field-observed liquefaction.
2. Cross-validation was not used. Metrics reported were based upon a single randomized split. The use of k-fold cross-validation (with either  $k=5$  or  $k=10$ ), as well as repeated stratified k-fold is suggested in future studies to provide tighter bounds for the variance associated with the estimated values; also, it will be easier to identify when models have fit the data too closely (i.e., an indication that there may be some degree of overfitting) especially for the unconstrained DT.
3. [3] Using default parameters. The default hyperparameters from scikit-learn were used to train all three of these models. For example, the DT was allowed to grow indefinitely with no constraints on either the maximum depth or the minimum number of leaf nodes. This can lead to overfitting as we know. It would seem like an obvious next step to perform a formal grid search (or random search), and use this to evaluate both `max_depth` and `min_samples_leaf` for the DT, plus both `n_estimators` and `gamma` for the RF model. In addition, it seems that using cost complexity pruning for the DT should also be considered.
4. Inconsistent Split in the SVM Evaluation; The SVM splits were originally done using a 70/30 split of the data (`n_test` = 160), while the splits for DT and RF were done as an 80/20 split (`n_test` = 107); In order to compare each classifier fairly, future analyses will either need to be run with the same split scheme or, preferably, will use cross validation on the entire dataset.

Future work should therefore: (a) be able to build on a substantial expansion of the field CPT dataset to create an independent, field based test set; (b) Evaluate the performance of gradient boosted classifiers (XGBoost, LightGBM) and lightweight deep models (BiLSTM, 1-D CNN); (c) perform formal hyperparameter optimization under cross-validation for all models, including tree pruning; (d) generate interpretable, model agnostic explanations for the predicted hazard pattern by using SHAP or permutation based feature importance in addition to explicitly displaying the decisions made by the decision trees.

## 4. CONCLUSION

The three supervised classifiers, decision tree, random forest, and support vector machine, were used on a 532-point data set created using fuzzy GIS/CPT anchored labels for four spatial predictors (Vs30, PGA, GWL, and slope) to generate a city-wide liquefaction hazard map for Samarinda. Based on the performance of each classifier on the test set, the decision tree produced the highest weighted accuracy (87%) and the highest weighted F1 (0.87), compared with SVM (80%, 0.80) and RF (78%, 0.78). The decision tree-based hazard map shows that about 68% of Samarinda's area falls into the very low class, while 6% fall into the low class, 7% into the high class, and 19% into the very high class. This hazard map also shows that most areas classified in the very-high zone are located in the eastern part of Samarinda, where soils are Sulfaquent, recent alluvial deposits are present, and shallow groundwater is present. The local positive correlation between Vs30-hazard can be explained as an artifact arising from the use of regional predictive variables rather than as evidence of a physical basis for liquefaction.

Although this is a good start, it has some serious limitations that need to be addressed. First, many of the labels for the training data came from a Fuzzy GIS Proxy Map and therefore do not reflect actual site investigations. Second, although the unconstrained Decision Tree showed signs of "over-fitting," which would limit its reliability. Therefore, these results should be considered a preliminary screening tool and/or decision-support tool; they cannot replace individual site-specific geotechnical investigations. The authors recommend developing the field CPT database substantially and incorporating the methodology improvements mentioned in section 4 (cross-validation, hyper-parameter tuning, Gradient Boosted Models and Deep Learning Models, feature importance, and visualization of trees) before using these maps directly as input into municipal land use planning or code development.

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