INTEGRATION OF EXPLAINABLE ARTIFICIAL INTELLIGENCE TO IDENTIFY SIGNIFICANT LANDSLIDE CAUSAL FACTORS FOR EXTREME GRADIENT BOOSTING BASED LANDSLIDE SUSCEPTIBILITY MAPPING WITH IMPROVED FEATURE SELECTION

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ABSTRACT

Landslides have been a regular occurrence and an alarming threat to human life and property in the era of anthropogenic global warming. An early prediction of landslide susceptibility using a data-driven approach is a demand of time. In this study, we explored the eloquent features that best describe landslide susceptibility with state-of-the-art machine learning methods. In our study, we employed state-of-the-art machine learning algorithms including XgBoost, LR, KNN, SVM, Adaboost for landslide susceptibility prediction. To find the best hyperparameters of each individual classifier for optimized performance, we have incorporated the Grid Search method, with 10 Fold Cross-Validation. In this context, the optimized version of XgBoost outperformed all other classifiers with a Cross-validation Weighted F1 score of 94.62%. Followed by this empirical evidence, we explored the XgBoost classifier by incorporating TreeSHAP and identified eloquent features such as SLOPE, ELEVATION, TWI that complement the performance of the XGBoost classifier mostly and features such as LANDUSE, NDVI, SPI which has less effect on models performance. According to the TreeSHAP explanation of features, we selected the 9 most significant landslide causal factors out of 15. Evidently, an optimized version of XgBoost along with feature reduction by 40%, has outperformed all other classifiers in terms of popular evaluation metrics with a Cross-Validation Weighted F1 score of 95.01% on the training and AUC score of 97%.

Keywords  Feature Reduction, Landslides, Machine Learning, SHAP, XGBoost

1 Introduction

Landslides are subject to a great concern for Geological and Environmental researchers from all over the world due to its irreparable and execrable impact on environment, society and economy. Landslide is a natural calamity which is characterized by the movement of a mass rock, debris or earth down a slope. Several environmental factors like heavy rainfall, geographical factor like location, land near volcanoes etc contribute to the occurrence of landslides. Especially, in some areas, Rainfall, slope, Land Use and Land Cover Change, and Elevation etc are one of the most influencing factors for Landslide (Mind’je et al., 2020). Hilly and Coastal areas all over the globe are mostly vulnerable to frequent and most devastating landslides. More than thousand people are killed by landslides every year around the globe, including an average of 25 - 50 deaths all alone in United States (Survey, 2021). According to the study of
ANN (Artificial Neural Network) in some studies (Chen et al., 2018; Kalantar et al., 2018). A novel machine learning Autoencoder based model outperformed the traditional models for extracting optimal non-linear features from environmental factors. As a result, over the years a decent number of state of art studies have been conducted for Landslide Susceptibility Mapping with Machine Learning, Deep Learning and Artificial Neural Networks. The immense potential of Machine Learning algorithms can be utilized to automate and improve the efficiency of the analysis and prediction of Landslide Susceptibility (Sahin et al., 2020).

Machine Learning methods including Naïve Bayes (NB), Multilayer Perceptron (MLP), Kernel Logistic Regression (KLR), and J48-bagging was employed for Landslide Susceptibility Mapping considering the area of Youfang district, China in the study of Hong et al. (2019) and it is observed from the study that MLP (Multilayer Perceptron) outperformed all other classifiers and proved to be an efficient tool for landslide study of this area. Sabana et al. (2020) proposed a hybrid neural network classifier integrating Multilayer Perceptron (MLP) and Bagging for an efficient mapping of rainfall induced landslides to support identification of vulnerable areas for disaster prevention and management. Several other studies have also found that Multilayer Perceptron (MLP) or a hybrid combination of Multilayer Perceptron (MLP) and Particle Swarm Optimization is an compelling classifier in the study of Landslides (Pham et al., 2017; Li et al., 2019). Deep Learning algorithms excel the study of Landslide Susceptibility prediction and analysis due to their deep architectures supporting robust in-built feature extraction strategies and great capacity to tackle confounding and sensitive factors. Huang et al. (2020a) found in their study that a Fully Connected Sparse Autoencoder based model outperformed the traditional models for extracting optimal non-linear features from environmental factors. Moreover, a spatially explicit deep neural network was proposed by Dao et al. (2020), where for feature selection Relief-F method was integrated to quantify the utility of the conditioning factors. Deep Neural Networks found to be comparatively outperforming over the conventional machine learning classifiers in the domain of Landslide Susceptibility in several other state of art studies (Bui et al., 2020; Zhu et al., 2020).

Though Deep Learning based methods can efficiently predict Landslides, the architectures of these algorithms are complex in structure and computationally expensive. Even for training purpose, to build an effective model, deep neural networks need a large amount of training data.

In this context, to find an efficient but less computationally expensive framework for Landslide study, researchers have studied the potential of Ensemble based, Probabilistic and Hybrid Machine Learning classifier for Landslide Susceptibility Prediction. Bagging based Reduced Error Pruning Trees (BREPT), a novel hybrid machine learning classifier, was proposed by Pham et al. (2019) with notable performance in Landslide Susceptibility. Similarly, another tree based hybrid classifier was proposed by Thai Pham et al. (2019) with impressive AUC scores. Also, Classification and Regression Tree (CART) algorithm outperformed Multilayer Perceptron based classifiers in some recent studies (Huang et al., 2020b). Some state art studies outlined the extreme potential of ensemble based or gradient boosting based machine learning classifiers through comparative analysis of ensemble machine learning methods and gradient boosting algorithm with several other methods (Fang et al., 2021; Sahin 2020). Tree based ensemble algorithms showed prominent performance; Random Forest leading with impressive results in the study of Merghadi et al. (2020). Hybrid Random Forest based models with GeoDetector and RFE for factor optimization were developed by Zhou et al. (2021). Extreme Boosting algorithms tends to outperform in comparison with linear classifier by robust feature extraction and ability to deal with outliers (Rabby et al., 2021). However, Support Vector Machine and Logistic Regression exhibited significant performance in Landslide Susceptibility prediction and also outperformed ANN (Artificial Neural Network) in some studies (Chen et al., 2018; Kalantar et al., 2018). A novel machine learning method with the integration of unsupervised machine learning method K-Means Clustering and supervised Decision Tree based classifier was proposed by Guo et al. (2021).

Despite a large number of outstanding researches have been conducted on Landslide Susceptibility using Machine Learning and Deep Learning methods, no study have solved the issue of explainability of these state of art Artificial Intelligence researchers. Considering the exigency of an early and automated prediction of Landslides, along with Geologists and Environmental scientists, AI (Artificial Intelligence) researchers from all over the world has devoted themselves in the extensive study of Landslide Susceptibility Mapping using Artificial Intelligence based methods. As a result, over the years a decent number of state of art studies have been conducted for Landslide Susceptibility Prediction. A new approach has been proposed by Sultana (2020), considering the time period of 2000-2018, the yearly average number of landslides in Bangladesh is 19, with a 4% rate of increase per year, which ultimately results in 38 fatalities and 54 injuries on average. Landslides often damage road networks in hilly areas causing great direct or indirect consequential economic losses due to hindrance in communication with the hilly parts of a country (Winter et al., 2016). Landslides are great threat to socio-economic conditions of a country (Perera et al., 2018). The impact of a landslide may be extended to destruction of important infrastructure, cultivable land and natural resources. It may lead to blockage of rivers and intensify the risk of floods (FAO, 2021). The study Landslide Susceptibility is sensitive and arduous due to the presence of uncorrelated or non-linearly correlated environmental factors responsible for Landslides (Huang et al., 2020a). In this context, an extensive statistical data driven analysis could help us to detect useful hidden and confounding patterns for identification of landslides to support effective measures to prevent this disaster.

In recent years, the global issue of Landslide, an alarming threat to mankind, has drawn attention of the Artificial Intelligence researchers. Considering the exigency of an early and automated prediction of Landslides, along with Geologists and Environmental scientists, AI (Artificial Intelligence) researchers from all over the world has devoted themselves in the extensive study of Landslide Susceptibility Mapping using Artificial Intelligence based methods. As a result, over the years a decent number of state of art studies have been conducted for Landslide Susceptibility Prediction. Bagging based Reduced Error Pruning Trees (BREPT), a novel hybrid machine learning classifier, was proposed by Pham et al. (2019) with notable performance in Landslide Susceptibility. Similarly, another tree based hybrid classifier was proposed by Thai Pham et al. (2019) with impressive AUC scores. Also, Classification and Regression Tree (CART) algorithm outperformed Multilayer Perceptron based classifiers in some recent studies (Huang et al., 2020b). Some state art studies outlined the extreme potential of ensemble based or gradient boosting based machine learning classifiers through comparative analysis of ensemble machine learning methods and gradient boosting algorithm with several other methods (Fang et al., 2021; Sahin 2020). Tree based ensemble algorithms showed prominent performance; Random Forest leading with impressive results in the study of Merghadi et al. (2020). Hybrid Random Forest based models with GeoDetector and RFE for factor optimization were developed by Zhou et al. (2021). Extreme Boosting algorithms tends to outperform in comparison with linear classifier by robust feature extraction and ability to deal with outliers (Rabby et al., 2021). However, Support Vector Machine and Logistic Regression exhibited significant performance in Landslide Susceptibility prediction and also outperformed ANN (Artificial Neural Network) in some studies (Chen et al., 2018; Kalantar et al., 2018). A novel machine learning method with the integration of unsupervised machine learning method K-Means Clustering and supervised Decision Tree based classifier was proposed by Guo et al. (2021).

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Intelligence algorithms. As the structure of these state of art algorithms are very complex from a mathematical point of view, it often engenders a BlackBox problem which may sometimes lead to the inefficiency of these framework in the future. And also, no previous studies have dedicatedly investigated the possibility of successful prediction of Landslides using less number of geological and topological factors with the help of machine learning based automated systems. In this concern, in this study, we have employed Explainable Artificial Intelligence framework for predicting Susceptibility of Landslides. The key contributions of this study are as follows;

- Identification of most important geological, topological and hydrological factors that best corroborate the performance of automated machine learning model for the assessment and early prediction of Landslide Susceptible Area.
- Extensive performance analysis of machine learning classifiers to identify most suitable Machine Learning algorithm for landslide susceptibility mapping.
- Proposal of an optimized integrated ensemble based machine learning solution which needs less number of landslide causal features to efficiently classify Landslides by reducing costs and time consumed in the primary stage Landslide related studies.

2 Methods

In this section, an illustration of the methods that implied in our study, have been delineated in a detailed manner. The research framework of our study is graphically represented at Figure 1.

Figure 1: Our Research Framework

2.1 Normality Test

Normality test is a statistical analysis-based method that is used to determine whether or not the distribution of data follows a Gaussian Distribution. In data mining, it is often important to comprehend the distribution of data that helps to discern whether to use parametric or non parametric statistical methods for exploratory data analysis. If the data follows a Gaussian distribution, then parametric statistical methods are incorporated, else non-parametric statistical methods are incorporated. In this context, to understand the data distribution of our feature variables involved in Landslide Susceptibility prediction we employed a popular and reliable normality evaluation method (Yap and Sim, 2011), Sharpio-Wilks, that generates p-values based on test statistics (W-statistic). The W-statistic or test statistic is computed as (Royston, 1992):

\[
W = \frac{\left( \sum_{i=1}^{n} a_i x_i \right)^2}{\sum_{i=1}^{n} (x_i - \bar{x})^2}
\]  

(1)
Where $W$ denotes the test statistic value, $x_{(i)}$ denotes the $i$th order statistic and $\mu$ denotes the mean of the sample. And also, $a_i$, the coefficient can be stated as:

$$ (a_1, \ldots, a_n) = \frac{m^TV^{-1}}{C} $$  

(2)

Here $C$ is a vector norm that can be donated by:

$$ C = \|V^{-1}m\| = (m^TV^{-1}V^{-1}m)^{1/2} $$  

(3)

The following Table 1 represents the W-Statistic values computed through the Sharpio-Wilks test for each individual feature variable of our dataset.

| Feature Name | W-Statistic | Feature Name | W-Statistic |
|--------------|-------------|--------------|-------------|
| PROFILE      | 0.752       | SLOPE        | 0.771       |
| PLAN         | 0.636       | ASPECT       | 0.864       |
| CHANGE       | 0.685       | TWI          | 0.868       |
| LANDUSE      | 0.665       | SPI          | 0.749       |
| ELEVATION    | 0.735       | DRAINAGE     | 0.809       |
| NDVI         | 0.857       | ROAD         | 0.642       |
| RAINFALL     | 0.818       | GEOLOGY      | 0.847       |
| FAULTLINES   | 0.684       |              |             |

Table 1: Sharpio-Wilk Test Statistic of Feature Variables

P-values illustrate that from a given data sample how likely the data was drawn from a Gaussian distribution based on a certain threshold. Evidently, a p-value less than or equal to the threshold value of 0.05 delineates that data sample does not follow a normal or Gaussian distribution and a p-value greater than 0.05 delineates that data was drawn from a normal distribution. In this study, based on the normality test analysis, we found that the data samples from any individual independent variable were not drawn from a normal distribution. However, numerous characteristics of the dataset are continuous in nature when it comes to the area of Geotechnical Engineering, which is poorly reflected by the data distribution. According to this research, a linear machine learning model would not be the best match to capture complicated multi-co-linearity difficulties when applied to a different dataset’s global point of view. Considering the analysis, we successfully applied the geotechnical engineering domain to identify the best potential machine learning solution throughout our study.

2.2 Chi-Square Test

In data mining and inference based research, it is important to understand whether or not a certain feature contributes to the final outcome. The statistical feature significance test helps us to identify and select features that strongly corroborate the final prediction. In Geo-technical Science, identifying key factors that best predict a Landslide Susceptibility is an indispensable part. In our study, we decided to employ a non-parametric statistical significance-based test, the Chi-Square test, to identify the importance of our feature variables in Landslide Susceptibility prediction based on the normality test results. The Chi-Square test is a non-parametric statistical significance analysis method that is suitable for analyzing the significance of independent variables. To state mathematically (Singhal and Rana, 2015; McHugh, 2013),

$$ X_c^2 = \sum_{i=1}^{N} \frac{(O_i - E_i)^2}{E_i} $$  

(4)

Here, $c$ denotes "Degree of Freedom", $O$ denotes "observed value" and $E$ denotes "expected value", and $i$ is the "ith" position is in the contingency table. The value of $c$ is computed through,

$$ c = (N_d - 1) \times (N_f - 1) $$  

(5)

Here, $N_d$ denotes "Number of Data Instances" and $N_f$ denotes "Number of Features". Afterward, we determine the statistically significant P-values for the independent variable against the dependent variable using the computed Chi-Square and degree of freedom values. The p-values computed through the Chi-square test are shown in Table 2. According to the p-value threshold of 0.05, we can infer that all of our feature variables show statistical evidence to espouse the prediction of Landslide Susceptibility.
Table 2: p-value Scores From Chi-Square Test

| Feature Name | P-Value | Feature Name | P-Value |
|--------------|---------|--------------|---------|
| PROFILE      | 3.19E-94| SLOPE        | 9.73E-291|
| PLAN         | 1.13E-123| ASPECT      | 4.04E-17 |
| CHANGE       | 1.24E-57| TWI          | 2.89E-308|
| LANDUSE      | 6.56E-158| SPI         | 8.93E-11 |
| ELEVATION    | 7.11E-162| DRAINAGE    | 7.77E-17 |
| NDVI         | 9.96E-98| ROAD         | 0       |
| RAINFALL     | 6.00E-82| GEOLOGY      | 4.32E-88 |
| FAULTLINES   | 1.27E-48|              |         |

Here, a p-value of less than or equal to 0.05 indicates that the particular categorical feature variable significantly contributes to the classification of Landslide Susceptibility with strong statistical evidence.

2.3 Machine Learning Classifiers

In our study, we have employed 5 machine learning algorithms for experimental purpose and optimized their performance considering popular evaluation metrics.

2.3.1 Support Vector Machine

Support Vector Machine (SVM) is a machine learning classifier which works in a supervised manner. It delineates a boundary to disparate the data point through analyzing the datapoints from training set based on differences in data distribution across individual classes. This boundary is called decision boundary which helps to classify between classes like Landslide Susceptible or Non-Landslide Susceptible. The decision boundary of SVM is a hyperplane in an N-dimensional space which evidently classifies the data points of different classes. Data points that are closer to the hyperplane and evinces a significant impact on the hyperplane’s direction and orientation are called support vectors. The performance of the SVM is optimized through support vectors. The weights associated with these support vectors corroborates the classifier to shape to orientations of the hyperplane. SVM is an empirically popular classifier that has exhibited noteworthy performance in the domain of Landslide Susceptibility Mapping (Huang and Zhao, 2018).

SVM can be further divided into two major categories, Linear SVM and Non-Linear SVM. The category of SVM is decided based on the kernel function it uses to draw the hyperplane. In Non-Linear SVM, the radial basis function is computed as, for Kernel, K,

\[ K(x, y) = e^{-\frac{|x-y|^2}{\sigma^2}} \]  

(6)

Where \( x \) and \( y \) are data points and \( \sigma \) is a free parameter that controls the degree of generalization. For better optimization, the generalization parameter and kernel function is tweaked to find the combination that best supports the classification of Landslide Susceptibility.

2.3.2 Logistic Regression

Logistic Regression is a linear machine learning classifier, well suitable for handling categorical and numerical feature variables and capable of robustly predicting binary outcomes. Logistic Regression implies a log odds ratio which is an iterative maximum likelihood method to predict whether a given set of features belongs to a certain class. Logistic Regression follows the logistic function or sigmoid function to draw a decision boundary between the two classes, Landslide Susceptible area and Non-Landslide Susceptible area. For an uni-variate logistic regression, To state mathematically,

\[ y = \frac{e^{(w_0 + w_1 x)}}{1 + e^{(w_0 + w_1 x)}} \]  

(7)

Where, \( y \) is target variable, \( w_0 \) indicates bias and, \( w_1 \) indicates the coefficient or weights of feature variable \( x \). Logistic Regression is widely used in the domain of Landslide Susceptibility Mapping due to it’s simple structure and effective performance for binary classification problems (Lombardo and Mai, 2018).
2.3.3 K Nearest Neighbours

K Nearest Neighbours (KNN) is a non-parametric machine learning algorithm. It is also called a lazy learning algorithm, much suitable for smaller datasets (Guo et al., 2003). To classify data instances into a certain category, KNN employs a neighbourhood similarity analyzing method incorporating distance metrics like Manhattan Distance, Euclidean Distance etc, to successfully create discriminating supervised clusters of individual class labels like Landslide Susceptible or Non-Landslide Susceptible. For final classification of Landslide Susceptibility, it would follow a majority voting criteria, considering the class labels of a certain number of nearest neighbours based on the results of distance metrics analysis. The generalized formula of computing distances for KNN is:

\[
\text{Distance} (X, Y) = \left( \sum_{i=1}^{n} |x_i - y_i|^p \right)^{\frac{1}{p}}
\]  

Here, \( x \) and \( y \) are datapoints of according feature variable and target variable, and \( p \) controls which distance metrics to be used. For Manhattan Distance \( p \) is set to 1 and for Euclidean Distance \( p \) is set to 2.

2.3.4 AdaBoost

Adaptive Boosting (AdaBoost) is a tree based machine learning classifiers, which aggregates multiple weak learners (decision trees) in an ensemble manner to build a robust classifier (Freund and Schapire, 1997). A single decision tree or weak learner in Adaboost is called a stump which has maximum depth of 1 with one root and two leaves. The algorithm assigns more weight on difficult to classify instances and less on those which are well classified. Thus, it creates a forest of stumps to efficiently classify a Landslide Susceptible and Non-Landslide Susceptible area. The amount of say for each stump is determined based on the classification error which is basically the sum of weights for incorrectly classified samples (Schapire, 2013). The number stumps to use for classification has a significant impact on the classification performance. It is an extremely fast classifier compared to other tree based classifier which makes it a strong candidate for landslide susceptibility prediction.

2.3.5 Extreme Gradient Boosting(XgBoost)

Extreme Gradient Boosting (XgBoost) algorithm is a tree based ensemble learning classifier that solves the overfitting issue previously present in decision tree-based classifiers with its improved gradient boosting strategy with built-in regularization and impressive gains in speed (Chen and Guestrin, 2016). The improved regularization strategy makes this algorithm so robust that it has evinced notable performance for solving problems that include a large amount of unstructured data (text, images, etc) or dataset containing outliers and features that are sensitive in nature (Khan Inan et al., 2021). In comparison to the previous general Gradient Boosting (GBM), a number of new design features such as robustness in handling missing values, approximate and sparsity aware split-finding algorithm, parallel computing, cache-aware access, block compression, and sharding have made Xg Boost an effective choice for complex and sensitive classification problems.

The gradient descent method is employed to build every decision trees uniquely, followed by beginning with a certain threshold and modifying the weights in an iterative manner by minimizing residuals in every single iteration. So, the trees built after every iteration remains unique as the error or mistakes done by the previous tree is minimized or regularized in the next tree to build.

Mathematically, residuals are calculated to tackle the problem of unique trees. Residuals are errors between observed and predicted values. Each tree starts with a single leaf and all of the residuals go to the leaf.

\[
\text{Cover,C} = \sum_{i=1}^{N} [P(\text{lf})i(1 - P(\text{lf})i)]
\]

Here, \( P(\text{lf}) \) denotes previously predicted probability for ith leaf. Similarity Score, \( S \), is calculated for each new leaf.

\[
S = \frac{\sum_{i=1}^{N} R}{C + \lambda}
\]

Here, in equation of \([10]\), \( \lambda \) is the regularization parameter that controls pruning of trees, and \( R \) and \( C \) denotes residuals and cover accordingly.

The Gain of the trees are computed through calculating the similarity scores of left, right and root nodes. It tells us to where to split the data.

\[
G = L_S + R_S - N_S
\]
Here, $G$ stands for Gain, $L_S$, $R_S$, $N_S$ denote accordingly, similarity score of Left, Right and Root Node. Considering
the immense potential of Extreme Gradient Boosting algorithm we adopted the algorithm for our study of Landslide
Susceptibility Prediction.

2.4 Exhaustive Grid Search

Grid Search is an exhaustive searching method popularly used for hyperparameter tuning of Machine Learning
algorithms. This method incorporates grid based parameter search by which it computes every possible combination
of parameters from a given set of values. It helps to optimize the performance along with reducing overfitting issue
of Machine Learning algorithms to build an efficient classifier based on certain data. In our study, to optimize the machine
learning algorithms for landslide susceptibility prediction, we have incorporated the Grid Search method for finding
best hyperparameters for every individual classifiers validating by 10-Fold Stratified Cross Validation of Weighted F1 Scores. The grid of hyperparameters which has been optimized with Grid Search depicted in the Table

| Classifier | HP         | Definition                          | Parameters Grid          |
|------------|------------|-------------------------------------|--------------------------|
| XgBoost    | max_depth  | Maximum Depth of a Tree             | [2,3,5,6,8]              |
|            | n_estimators | Number of trees                      | [500, 1500, 3000, 5000]  |
|            | learning_rate | Learning Rate                       | [0.01, 0.1, 0.05, 0.3, 0.5] |
|            | gamma      | Regularization Parameter            | [0, 0.1, 0.5, 1, 2]      |
|            | subsample  | Percentage of Training Rows          | [0.5, 0.7, 0.8, 0.9, 1]  |
| KNN        | n_neighbors | Number of Neighbours                | [3, 5, 7, 9, 11, 13]     |
|            | p          | Exponent of Minkowski distance       | [1, 2]                   |
| LR         | C          | Regularization Parameter            | [0.001, 0.01, 0.1, 1, 10, 100] |
|            | solver     | Algorithm to use                     | ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'] |
|            | penalty    | Regularization Algorithm            | ['ll', 'l2', 'elasticnet'] |
| SVM        | C          | Regularization Parameter            | [0.01, 0.1, 1, 10, 100]  |
|            | kernel     | Kernel Trick                        | ['linear', 'rbf']        |
| Adaboost   | n_estimators | Number of trees                      | [0.001, 0.01, 0.1, 0.15, 0.2, 0.3, 0.5, 1] |
|            | learning_rate | Learning Rate                       | [10, 50, 100, 500, 1000, 1500, 3000] |

Table 3: Range of Hyperparemeters (HP) and Definition

2.5 TreeSHAP Explanation

TreeSHAP is an extension of SHAP (SHapley Additive exPlanations) method which elucidates the prediction or output
of Machine Learning algorithms by computing Shapley values for a given data instance that delineates what is the sum
of contributions from it’s individual feature variables (Lundberg and Lee [2017] Lundberg et al. [2018]). It is a game
theoretic approach instigated as a fast and model-specific alternative to KernelSHAP for decision tree based algorithms.
Shapley values, a coalitional game theory technique, illustrates how to allocate the prediction of individual instances
among the characteristics in a fair manner. Shapley values are computed as (Molnar [2021];

$$\phi_i = \sum_{S \subseteq N - i} \frac{|S|!(M - |S| - 1)!}{M!} [f_x(S \cup i) - f_x(S)]$$

(12)

Here, $f(x)$ denotes prediction function of Machine Learning classifier and $M$ stands for total number of features.$S$
represents any subset of features that don’t include the $i$ – $th$ feature and $|S|$ is the size of that subset.

In our study, we have incorporated TreeSHAP method for analyzing the predictions of Extreme Gradient Boosting
algorithm to solve the blackbox issue of machine learning algorithms in a motivation to build Explainable Artificial
Intelligence based solution along with identifying which of the features corroborates mostly an effective classification of Landslide Susceptibility.

3 Experimental Results

3.1 Dataset Description

In our study, we have experimented our research methods on a benchmark dataset of Landslide Susceptibility Mapping considering three Upazilas of Rangamati Hill District, Bangladesh which was prepared by Rabby et al. (2021). This district is extremely susceptible to landslides due to its geographical location and several natural factors. The natural climate factors like heavy rainfall and geographical factor-like the highest average slope gradients have made this district prone to landslides and a convincing candidate in terms of the study area for landslide research. The following dataset contains 196 data instances of each of the two target classes, Landslide Susceptible and Non-Landslide Susceptible. 15 important Geological, Topological and Hydrological factors for Landslide Susceptibility Mapping are presented in this dataset. In our study, we have included these 15 landslide causal factors as feature variable for predicting Landslide Susceptibility. The following feature variables are; 'PROFILE' (Profile Curvature), 'PLAN' (Plan Curvature), 'CHANGE', 'LANDUSE', 'ELEVATION', 'SLOPE', 'ASPECT', 'TWI', 'SPI', 'DRAINAGE' (Distance from Drainage Network), 'NDVI' (Normalized Vegetation Index), 'RAINFALL', 'FAULTLINES' (Distance to Fault lines), 'ROAD' (Distance to Road Network), 'GEOLOGY'. Table 4 delineates the methods utilized to compute these landslide causal factors by incorporating remote sensing technologies (Abedin et al., 2020). A brief description of the features which have been analyzed and utilized in this study are given below:

| Landslide Casual Factor     | Methods Used to Determine the Factor                                                                 |
|-----------------------------|-----------------------------------------------------------------------------------------------------|
| PROFILE CURVATURE           | ArcGIS Curvature Function                                                                         |
| PLAN CURVATURE              | ArcGIS Curvature Function                                                                         |
| LAND COVER CHANGE           | Anderson scheme Level-I method (Satellite Images)                                                 |
| LANDUSE CHANGE              | Anderson scheme Level-I method (Satellite Images)                                                 |
| ELEVATION                   | Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Map (GDEM) |
| NDVI                        | LandSat 8 level 2 imagery                                                                         |
| RAINFALL                    | Kriging Interpolation                                                                             |
| FAULTLINES                  | Euclidean Distance tool in ArcGIS                                                                 |
| SLOPE                       | Slope tool in ArcGIS                                                                              |
| ASPECT                      | Aspect tool in ArcGIS                                                                             |
| TWI                         | ASTER GDEM                                                                                        |
| SPI                         | ASTER GDEM                                                                                        |
| DRAINAGE                    | Euclidean Distance tool in ArcGIS                                                                 |
| ROAD                        | Euclidean Distance tool in ArcGIS                                                                 |
| GEOLOGY                     | Geological Survey                                                                                 |

Table 4: Methods To Compute Landslide Causal Factors

3.1.1 PROFILE (Profile Curvature)

PROFILE (Profile Curvature) is an important factor used in the study of Landslide Susceptibility Mapping. The curvature in the downslope direction along a line produced by the intersection of an imaginary vertical plane with the ground surface is known as Profile Curvature. The driving and resistive strains within a landslide in the direction of motion are affected by profile curvature. (Carson and Kirkby, 1972; Meten et al., 2015). The data count distribution of the feature PROFILE is depicted in Figure 2.

3.1.2 PLAN (Plan Curvature)

The curvature of topographic contours or the curvature of a line generated by the intersection of an imaginary horizontal plane with the ground surface is referred to as Plan Curvature (PLAN). The convergence or divergence of landslide
material and water in the direction of landslide motion is controlled by plan curvature (Ohlmacher, 2007; Meten et al., 2015). The data count distribution of the feature PLAN is depicted in Figure 3.

3.1.3 CHANGE

The loss of natural areas, notably forests, to urban or suburban development, or the loss of agricultural regions to urban or exurban development is referred to as land cover change (CHANGE) (Sealey et al., 2018). A number of studies have found that land cover change (CHANGE) is a notable and strongly influencing factor towards determination of the susceptibility of Landslides for a particular area (Promper et al., 2014; Restrepo and Alvarez, 2006). The data count distribution of the feature CHANGE is depicted in Figure 4.

3.1.4 LANDUSE

Land use is usually described as a sequence of human-performed activities on land with the goal of obtaining goods and advantages from the usage of land resources (Reichenbach et al., 2014). In the hilly or mountainous areas, Land use change (LANDUSE) can increase or decrease the possibility of landslides with potential influence (Chen et al., 2019). The data count distribution of the feature LANDUSE is depicted in Figure 5.

3.1.5 ELEVATION

Landslide vulnerability is frequently assessed using elevation. The altitude of terrain is referred to as elevation. According to Dou et al. (2015), the ground at various heights will have varying levels of sensitivity which is a key factor to identify the probability of possible Landslide events. The data count distribution of the feature ELEVATION is depicted in Figure 6.
3.1.6 SLOPE

The angle measured between a horizontal plane and a particular location on the ground surface is known as the slope angle (SLOPE) (Whitworth et al., 2011). SLOPE is one of most influential factors that can lead to causing serious landslides. SLOPE also has a notable correlation with other geological and topological factors which made it an early alarm to assess the susceptibility of landslides in the hilly parts of the world. In general, the likelihood of a landslide rises as the slope rises (Meten et al., 2015). The data count distribution of the feature SLOP is depicted in Figure 7.

3.1.7 ASPECT

The aspect at a location on the ground surface, according to some researchers, is the direction that the tangent plane passing through that point faces and is represented in degrees. The aspect, in its most basic form, is a data type that indicates the geographical direction in which the slopes grow (Tanoli et al., 2017). The data count distribution of the feature ASPECT is depicted in Figure 8.

3.1.8 TWI

The Topographic Wetness Index (TWI), also known as the compound topographic indicator, is a wetness index that measures steady-state conditions. It is widely used to quantify the influence of topography on hydrological processes which has great influence in the occurrence of landslides (Mattivi et al., 2019). The data count distribution of the feature TWI is depicted in Figure 9.
3.1.9 SPI

The erosive force of a stream or water flow is measured by the SPI (Stream Power Index). The slope and contributing area are used to calculate SPI. SPI approximates the locations on the landscape where gullies are more likely to form (Abedin et al., 2020). The data count distribution of the feature SPI is depicted in Figure 10.

3.1.10 DRAINAGE

DRAINAGE refers to distance to drainage network. It is usually noticed that area near to drainage network are more prone to landslides which makes it a very crucial feature for the study of landslides (Abedin et al., 2020). The data count distribution of the feature DRAINAGE is depicted in Figure 11.
3.1.11 NDVI

The Normalized Difference Vegetation Index (NDVI) is used to calculate the density of green on a given plot of land. It measures vegetation by comparing the amount of near-infrared light reflected by vegetation to the amount of red light absorbed by vegetation. It has been identified as a good indicator of landslide susceptibility according to geotechnical researchers (Dahigamuwa et al., 2016). The data count distribution of the feature NDVI is depicted in Figure 12.

![Figure 12: Count Distribution of Data of NDVI](image)

3.1.12 RAINFALL

The amount of rainfall in a particular hilly area is a great indicator of landslide susceptibility. Excessive rainfall is often considered as a potential trigger for sudden and destructive landslides in the hilly regions (Abedin et al., 2020). Heavy rainfall can induce soil saturation, and debris flow can occur on certain slopes triggering the possibility of rainfall induced landslides (Chen et al., 2017). The data count distribution of the feature RAINFALL is depicted in Figure 13.

![Figure 13: Count Distribution of Data of RAINFALL](image)

3.1.13 FAULTLINES

Fault lines (FAULTLINES) are geological variables in a Landslides research that suggest tectonic breaks and reduce rock strength. In general, areas closer to the Faultline are more prone to landslides than areas further away (Regmi et al., 2014; Abedin et al., 2020). The data count distribution of the feature FAULTLINES is depicted in Figure 14.

![Figure 14: Count Distribution of Data of FAULTLINES](image)

3.1.14 ROAD

ROAD refers to the distance from the road of land that is a crucial measure to assess the landslide susceptibility of an area. Roads assist to concentrate drainage, while road cuttings harm the slope structure. Landslides near roadways might occur if the required precautions are not taken (Chen et al., 2017). The data count distribution of the feature ROAD is depicted in Figure 15.

![Figure 15: Count Distribution of Data of ROAD](image)
3.1.15 GEOLOGY

Geology is concerned with the permeability and strength of a region’s rocks and soil, and hence with landslides (Ayalew and Yamagishi, 2005). Understanding the geology of land area is always considered to be a crucial factor for effective study of Landslides. The data count distribution of the feature GEOLOGY is depicted in Figure 16.

In this study, the above mentioned 15 features has been taken into consideration for building a robust explainable machine learning model that best corroborates the prediction of Landslide Susceptibility adopting the geotechnical engineering domain. The study’s features have also been analyzed in various state-of-the-art investigations, with a high level of correlation in terms of landslide susceptibility mapping. Before employing the state of the art machine learning algorithms, we have spitted our dataset into a training and testing ratio of 67:33 with stratified sampling strategy and randomization seed of 15 using Scikit-Learn library.

3.2 Evaluation Metrics

In our study, to evaluate the performance of our machine learning models, we considered the analysis of below mentioned popularly used evaluation metrics.

- True Positive (TP): The case when the certain area is Landslide Susceptible and the model also classified as Landslide Susceptible.
- False Positive (FP): The case when the certain area is not Landslide Susceptible but the model classified as Landslide Susceptible.
- True Negative (TN): The case when the certain area is Not Landslide Susceptible and the model also classified as Not Landslide Susceptible.
- False Negative (FN): The case when the certain area is Landslide Susceptible but the model classified as Not Landslide Susceptible.
- Accuracy: It defines correctly classified areas with susceptible to Landslides. It can be computed as;

\[
\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{13}
\]

- Recall: It is defined as the ratio of the number of positive samples that have been correctly predicted as Landslide Susceptible corresponding to all Landslide Susceptible samples in the data. It can computed as;

\[
\text{Recall} = \frac{TP}{TP + FN} \tag{14}
\]
• Precision: It is defined as the ratio of the number of positive samples that have been correctly predicted as Landslide Susceptible corresponding to all samples predicted as Landslide Susceptible. It can be computed as:

\[
\text{Precision} = \frac{TP}{TP + FP}
\]  

(15)

• F1-Score: It is delineated as the term that balances between recall and precision. It can be defined as:

\[
F1 - \text{Score} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}}
\]  

(16)

### 3.3 Evaluation Stage 1: Optimization of Algorithms

In this section, we have optimized the performance of our Machine Learning classifiers using Grid Search method to find the best combination of Hyper-parameters for individual classifiers with 10-Fold Stratified Cross Validation to reduce the overfitting issue. We have employed the Scikit-Learn implementation in Python for SVM, KNN, Adaboost and Logistic Regression. And the Python Library of XgBoost for implementing the Extreme Gradient Boosting Algorithm. Grid Searching was performed by incorporating GridSearchCV method from popular Scikit-Learn library. In this stage of evaluation, all of the 15 feature variables have been employed for training and testing the individual classifiers. The best combinations of hyperparameters of the machine learning classifiers obtained through Grid Searching, are illustrated on the Table 5.

| Classifier | Hyperparameters |
|------------|-----------------|
| XgBoost    | max_depth=3     |
|            | n_estimators=3000|
|            | learning_rate=0.1|
|            | gamma=0         |
|            | subsample=0.7   |
| KNN        | n_neighbors=7   |
|            | p=1             |
| Logistic Regression | C=0.01     |
|            | solver='12'     |
|            | penalty='newton-cg' |
| SVM        | C=10            |
|            | kernel=rbf      |
| Adaboost   | n_estimators=1000|
|            | learning_rate=1|

Table 5: Best Combination of Hyperparameters

A graphical log-scale comparison of 10-Fold Stratified Cross-validation Scores with the obtained best hyper-parameters combination of the machine learning classifiers employed in our study is represented in the Figure 17.

![Cross Validation Scores with All Features](image)

Figure 17: Cross Validation Scores With All Features

The Confusion Matrix results of the machine learning classifiers on the test dataset is presented on the Table...
Table 6: Confusion Matrix Before Feature Reduction

|       | SVM | KNN | LR | AdaBoost | XgBoost |
|-------|-----|-----|----|----------|---------|
| TP    | 57  | 60  | 58 | 57       | 59      |
| FP    | 8   | 8   | 3  | 3        | 5       |
| TN    | 57  | 57  | 62 | 60       | 60      |
| FN    | 8   | 5   | 7  | 8        | 6       |

Table 7: Performance Evaluation with All Features

| Metrics       | SVM  | KNN  | LR   | AdaB | XgBoost |
|---------------|------|------|------|------|---------|
| Accuracy      | 87.69| 90   | 92.31| 90   | 91.54   |
| Precision (N) | 87.69| 91.94| 89.86| 88.24| 90.91   |
| Recall (N)    | 87.69| 87.69| 95.38| 92.31| 92.31   |
| F1 Score (N)  | 87.69| 89.76| 92.54| 90.23| 91.6    |
| Precision (P) | 87.69| 88.24| 95.08| 91.94| 92.19   |
| Recall (P)    | 87.69| 92.31| 89.23| 87.69| 90.77   |
| F1 Score (P)  | 87.69| 90.23| 92.06| 89.76| 91.47   |

In this context, based on the comparison of the performances of the individual machine learning classifiers, it is cleared that the optimized version of XgBoost (Extreme Gradient Boosting) is outperforming all other Machine Learning classifiers in evaluation criteria based on 10 Fold Stratified Cross Validation Mean F1 Weighted Scores. However, the findings on the test set demonstrate that the Logistic Regression model outperforms all other classifiers. But, as the logistic regression model does not outperform in terms of 10 Fold Cross Validation Scores, it may be deduced that the test dataset scores do not completely reflect the actual efficiency due to lack of the bulk of data samples. Apart from that, based on F1 Scores on test data samples, XgBoost is still showing the second best performance. Moreover, tree based gradient boosted methods have better explainability than other machine learning classifiers. Thus, in this evaluation stage, Optimized Extreme Gradient Boosting is identified as the most efficient algorithm to classify Landslide Susceptible area using the 15 feature variables from the utilized dataset.

3.4 Evaluation Stage 2: TreeSHAP Analysis

As optimized XgBoost is outperforming all other machine learning classifiers besides it has robust explainability, we further decided to proceed with the optimized XgBoost model for further analysis. In this stage of evaluation, we have integrated the TreeSHAP method with the optimized XgBoost (Extreme Gradient Boosting) Classifier (our best performing classifier from previous evaluation stage) to understand the prediction criteria of XgBoost and the level of contribution of individual features that strongly corroborate in Landslide Susceptibility prediction. Explainable Artificial Intelligence is an essential demand of present time as the complex and deep architectures of these machine learning models make it hard to interpret by engendering the BlackBox problem which is defined as not being able to detect where the model is actually looking or how much the individual features are contributing for a certain prediction. Considering the exigency and sensitivity involved in the study of Landslide Susceptibility, we interpreted the performance of XgBoost by analyzing the SHAP Feature Importance and SHAP Summary Plot.

3.4.1 SHAP Feature Importance

The SHAP Feature Importance plot illustrates the mean absolute shapley values for individual features. Figure 18 presents a graphical illustration of the mean absolute shapley values of all the features used for training the optimized Extreme Gradient Boosting (XgBoost) classifier before predicting Landslide Susceptibility. It is a bar plot where features are sorted in descending order based mean absolute SHAP values. Features with large absolute values like, SLOPE, ELEVATION, ROAD, TWI have significant impact on the prediction to support optimized XgBoost model for detecting Landslide Susceptible areas efficiently. On the other hand, FAULTLINES, PLAN, SPI, NDVI, LANDUSE have low absolute mean values indicating a very low influence in the model’s performance.

3.4.2 SHAP Summary Plot

The SHAP Summary Plot illustrated at Figure 19 combines feature importance with feature effects for the optimized XgBoost model of Landslide Susceptibility prediction. In the following summary plot, each point is a Shapley value for...
a feature and a data instance. Here, in the graph, the vertical axis delineates features sorted according to the level of influence in the model’s prediction and horizontal axis delineates Shapley values indicating the positive or negative correlation of the feature with the target variable. To understand the values graphically, a color-based comparison is drawn. The overlapping dots are jittered in the vertical axis direction which give us an idea of the Shapley value distribution per feature variable. The features are ranked in order of significance. The following summary plot strongly illustrates; SLOPE, ROAD and TWI as the most significant features with wide spread distribution along the horizontal axis supporting efficient prediction for Landslide Susceptibility. In contrast, instances of PLAN, NDVI and LANDUSE and some other features are not well distributed over the horizontal axis and possess a Shapley value of near to 0, indicating a very less or almost no influence on the model’s performance for Landslide Susceptibility Prediction.

The study of features’ contributions to the assessment of Landslide Susceptible region derived from TreeSHAP analysis can be validated by considering evidence from state-of-the-art studies by geo-science researchers. Firstly, Çellek (2020) has emphasized the importance of measuring Slope Angle (SLOPE) for classifying Landslides with strong evidences. Consequently, the optimized XgBoost model proposed in our study is also utilizing the SLOPE feature as the most significant feature for prediction of Landslides. Furthermore, ELEVATION has a great correlation with SLOPE in the study of Landslides and helps researchers to understand the vulnerability of an area towards Landslides. (Rabby et al.)
This fact has also been reflected in our investigation of Landslides through TreeSHAP analysis. Additionally, TWI and ROAD are also top contributing factors for assessing the susceptibility of Landslides which have been reflected in our model building process and studies by several geotechnical researchers (Chen et al., 2017; Abedin et al., 2020; Rabby et al., 2021). Thus, the following analysis strengthen the hypothesis of this study, and supports the proper adoption of Geoscience and Geotechnical Engineering domain at every stage of our proposed research framework.

3.5 Evaluation Stage 3: Improved Landslide Feature Selection

In machine learning-based solutions, feature reduction is extremely important. An efficient model that can forecast Landslides with high accuracy using only a few characteristics is a gift in the domain of geotechnical engineering for Landslide Susceptibility Mapping. From the evaluation scores of previous stages, the optimized version of XgBoost seems to be the best fit for portending landslide susceptibility. So, in this stage of experimental setup, we have elected XgBoost as our proposed model for integration in landslide susceptibility mapping and performed feature reduction for XgBoost using the analysis of SHAP values. For this, we have retrained XgBoost with Grid Searching and eliminated 6 features including ASPECT, FAULTLINES, SPI, PLAN, NDVI and LANDUSE which has comparatively a very low influence in the prediction of XgBoost model’s performance according to TreeSHAP analysis. The overall research methodology of proposed integrated optimized XgBoost model which can efficiently predict landslide susceptibility by using less number landslide causal factors is depicted in Figure 20.

Figure 20: The Complete Research Workflow for Building the Proposed Integrated XgBoost Model for Landslide Susceptibility Mapping using Less Number Landslide Causal Factors

Comparison of 10 Fold Stratified Cross Validation Mean Weighted F1 Scores before and after reduction of features illustrated in Figure 21.

It is clearly visible that after feature reduction the Cross Validation score of optimized XgBoost has been increased from 94.62% to 95.01%.

Table 8 delineates the final hyperparameter settings of the XgBoost model with reduced features.

Learning Curve helps us to determine whether or not increasing the amount of data is going to ameliorate the performance of model. The learning rate curve of XgBoost classifier from Figure 22 clearly depicts that there are room for improvement in the performance with more data in case of the optimized XgBoost model with reduced features. The point where the two lines in the graphs will converge, after that particular point the room for improvement with more data will be narrowed down.
Figure 21: Comparison of Cross Validation Scores of XgBoost with and without feature reduction

Table 8: Final Set of Hyperparameters of proposed optimized XgBoost model with Reduced Features

| Parameter Name | Value |
|----------------|-------|
| gamma          | 0     |
| learning_rate  | 0.1   |
| max_depth      | 3     |
| n_estimators   | 1500  |
| subsample      | 1     |

Figure 22: Learning Curve of XgBoost

Figure 23: ROC Curve of XgBoost
4 Discussion

In this study, after a rigorous analysis of machine learning classifiers for predicting Landslides in an automated manner, it is found that, optimized version of XgBoost classifier is a promising method which successfully adopts geotechnical engineering domain based on the outperforming results of Table 7 and Figure 17. Considering the massive potential of XgBoost model, this study further extended the research to explain the prediction criterion of XgBoost model by integrating TreeSHAP analysis in a motivation of solving the blackbox problem with Explainable Artificial Intelligence. According to the TreeSHAP analysis, 6 features were eliminated from the feature set and the XgBoost model was retrained along with exhaustive hyperparameter tuning. Here, after feature elimination, the 10 Fold Cross Validation Weighted F1 Score of XgBoost model has increased to 95.01%. It corroborates that feature reduction has been beneficial for the XgBoost model. Moreover, the optimized XgBoost model can generate outperforming results with even less features.

Reduction of features is a crucial contribution presented in this study that open doors for geoscience researchers to conduct effective studies on Landslides utilizing less features. The features that have been eliminated in the final model building process in this study can reduce the cost of the industry level works on the domain of Landslide Susceptibility prediction. For example, to compute the features like LANDUSE and NDVI, high-tech remote and satellite based technologies are required which increases the cost of the investigation and demands more time and technological manpower. In the primary stage, if the susceptibility of Landslide can be predicted without the need of these features which have high cost for computation purpose it is going to be great help for geotechnical researchers for both industry and academia. The optimized version of Xgboost with proposed architecture is outperforming other classifiers and previous settings of model even after eliminating the above mentioned 6 features. Due to the elimination of these 6 features, it would be possible to save more cost and time along with better utilization of the existing technological resources involved in Landslide study.

Comparatively, Optimized Extreme Gradient Boosting has outperformed all other machine learning classifiers even with reduction of 40% of the features with 10 Fold Stratified Cross-Validation Weighted F1 Scores of 95.01% and ROC-AUC score of 97%. It has also helped us to identify eloquent features that strongly corroborates in the prediction of Landslide Susceptibility. In this context, we prefer to adopt the optimized version of Extreme Gradient Boosting (XgBoost) with the identified eloquent features for Landslide Susceptibility Prediction using data-driven analysis.

From Figure 24, in comparison with the recent state of the art studies for Landslide Susceptibility Prediction using Artificial Intelligence based methods, the optimized XgBoost model with Reduced Features that outlined in our study, has outperformed the best model from the study of Rabby et al. (2021) by almost 6%, Mandal et al. (2021) by almost 4%, Sahin et al. (2020) by almost 8% and Huang et al. (2020b) by almost 10% in terms of AUC scores.

5 Conclusion

Landslides are another name of nightmare for the people living in the hilly areas from all over the world which causes a huge number of causalities every year exacerbating socio-economic condition along with unwanted death tolls. An early prediction of Landslide Susceptibility can be a great blessing for mankind. Realizing this exigency, we have performed extensive analysis to predict Landslide Susceptible area with state of the art Artificial Intelligence based methods. In our study, we have successfully identified the eloquent features which are most useful for an automatic and early prediction
Landslide Susceptibility with Machine Learning algorithms, through the integration of Explainable and Interpretable Artificial Intelligence, a milestone achieved in the study of Landslides and Geo-Technical science. Besides, due to the optimization of models and even with reduction of features our best performing model has outperformed the recent similar state of art studies and the previous study with similar dataset also. Moreover, this study also highlights that machine learning based feature selection is more suitable than the statistical analysis based feature selection in domain of Landslide study. The proposed model of this study, is a cost effective solution for the assessment and early prediction of Landslides at the primary investigation with less number of geological and topological features. Reduction of geological, topological and hydrological features would allow geotechnical researchers to conduct more economic and efficient research in less time. In future, we would like to collect more empirical data of Landslides and integrate state of art deep architectures including Generative Adversarial Networks (GANs) for more efficient and early prediction of Landslides to address the problem of Landslide Susceptibility Mapping for saving mankind from sudden catastrophes.

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