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MACHINE LEARNING FRAMEWORK FOR LANDSLIDE SUSCEPTIBILITY PREDICTION IN HILLY REGIONS

[1]Dr.Y Eswara Rao, [2]Dr Venkateswarlu Gogana, [3]Asmita Deb, [4]G.Prasanna Raj

[1]Professor of Civil Engineering & Principal, Dr.Samuel Gerogge Institute of Engineering &Technology Markapuram, Prakasham-District A.P, India.

[2]Professor, HoD & Chairman BoS, Department of Civil Engineering, Chaitanya Deemed to be University, Hyderabad, Telangana India.

[3]PG Scholar, Department of Urban and Regional Planning, School of Planning and Architecture JNAFAU,Masabtank, Hyderabad, Telangana, India.

[4]PG Scholar, Department of Urban and Regional Planning, School of Planning and Architecture JNAFAU,Masabtank, Hyderabad, Telangana, India.

[1]dr.ymeswar@gmail.com, [2]venkateswarlugogana@gmail.com, [3]asmitadeb1201@gmail.com, [4]goganaprasannaraj@gmail.com

Abstract: Landslides are one of the most destructive natural calamities in hilly and mountainous areas resulting in large scale loss of human lives as well as destruction of infrastructure and environment. Correct forecasting of areas vulnerable to landslides is of great importance for reduction of disaster risk and sustainable planning of land utilisation. In this paper, we propose a Machine Learning Framework for Landslip Susceptibility Prediction in Hilly Regions (MLF-LSHR) that combines geospatial, geological, hydrological and environmental factors for intelligent hazard assessment. The proposed framework uses multi-source datasets like Digital Elevation Models (DEM), rainfall data, soil properties, land-use types, vegetation indices, and past landslides inventories. Advanced machine learning algorithms such as Random Forest (RF), Support Vector Machine (SVM), Extreme Gradient Boosting (XGBoost) and Artificial Neural Networks (ANN) are used to model the complex relationships among the landslip conditioning factors. We combine data preprocessing, feature selection and spatial analysis techniques together to improve the prediction accuracy and model robustness. The framework generated landslip susceptibility maps with low, moderate, high and very high risk zones. The experimental evaluation shows that the ensemble based machine learning models have better predictive performance with high accuracy, precision, recall and Area Under the Curve (AUC) values as compared to the conventional methods. The proposed framework is an efficient decision support tool for disaster management authorities, urban planners and environmental agencies to implement proactive mitigation strategies and to improve resilience against landslip hazard in vulnerable hilly regions.

Keywords: Landslide Susceptibility Prediction, Machine Learning, Geographic Information System (GIS), Remote Sensing, Random Forest, XGBoost, Support Vector Machine, Artificial Neural Network,

1. INTRODUCTION

Landslides are among the world's most destructive natural hazards in hilly and mountainous areas. They cause huge loss of human lives, damage to infrastructures, environmental degradation and huge economic losses every year. The occurrence of landslip depends on a combination of geological, geomorphological, hydrological, climatic and anthropogenic factors. Landslip occurrences in many vulnerable areas have increased in frequency and intensity due to rapid urbanisation, deforestation, road construction, mining activities and climate change. Landslides pose a serious threat to sustainable development and disaster resilience in developing countries where settlements and transportation networks are often located in unstable mountain terrains. Thus, the precise identification of landslide-prone areas and the early assessment of susceptibility have become important components of disaster risk management and land-use planning. Main approaches to landslip susceptibility assessment include expert knowledge, field investigation, statistical analysis and heuristic methods. Although these approaches have been widely used for hazard zoning, they are often associated with subjectivity, limited scalability and challenges in processing large and complex geospatial datasets. Furthermore, the non-linear interactions between various landslip conditioning factors make it challenging to accurately model landslip occurrence patterns using traditional methods. As a result, scientists have increasingly turned to sophisticated computational methods that can process multidimensional environmental data and pinpoint complex links between contributing factors.

The recent advances of Remote Sensing (RS), Geographical Information Systems (GIS), Global Navigation Satellite Systems (GNSS) and Earth observation technologies provide large scale spatial and environmental datasets in landslip studies. Useful information to understand landslip mechanism and susceptibility pattern are provided by high resolution satellite images, Digital Elevation Models (DEMs), rainfall data, geological maps, land-use data and terrain features. The availability of these geospatial datasets paves new opportunities for the development of data-driven models for landslip prediction, which can contribute to accurate hazard assessment and disaster management planning. Machine Learning (ML) is a powerful analytical tool for landslip susceptibility prediction owing to its ability to learn complex patterns automatically from large datasets. Unlike traditional statistical methods, machine learning algorithms can efficiently simulate the nonlinear relationships of multiple landslip conditioning factors without explicit assumptions regarding the data distributions. Different machine learning algorithms such as Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), Artificial Neural Network (ANN), Extreme Gradient Boosting (XGBoost) and ensemble learning models have been successfully used for landslip susceptibility mapping . The algorithms have demonstrated enhanced prediction performance and robustness in forecasting high risk landslip zones across diverse geographical settings.

Among the developed machine learning techniques, ensemble learning algorithms are of great interest due to their ability to combine several predictive models and improve classification accuracy. Random Forest and XGBoost, in particular, have been very successful in dealing with high dimensional geospatial data and detecting important landslip conditioning factors. These algorithms efficiently handle heterogeneous environmental variables, missing data, overfitting and predict susceptibility reliably. In addition, the machine learning models provide quantitative measures of feature importance, allowing researchers to assess the relative importance of factors such as slope, rainfall, lithology, elevation, curvature, land use, and vegetation cover in the occurrence of landslips. Landslide susceptibility prediction is the estimation of the probabilities of future landslides occurrence with respect to historical landslide inventories and environmental conditioning factors. The general process of susceptibility assessment involves data acquisition, feature extraction, conditioning factor analysis, model training, validation and susceptibility mapping. Geographic Information System (GIS) has an important role to bridge between the spatial data and to visualise the susceptibility zones, so that the decision makers can locate the vulnerable areas and prioritise the risk reduction measures. The integration of GIS and machine learning greatly facilitates landslip hazard assessment, allowing for automatic analysis of large-scale spatial information and generation of high-resolution susceptibility maps. Climate change has further increased the demand for

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advanced landslip prediction systems. The intensification of rainfall, extreme weather phenomena and changing hydrological regimes in mountains areas make slopes unstable, thus increasing the risk of landslides. The environment is therefore subject to change due to the continued variability of climate, and classical hazard assessment approaches may not be able to deliver accurate future landslip scenarios. Machine learning based frameworks offer adaptive, data driven solutions that can continually integrate more environmental information and improve predictive accuracy over time. Machine learning has been providing a great deal of support for landslip susceptibility assessment but some challenges still exist. Much of the existing work has been limited to a small number of conditioning factors, small datasets or a single machine learning model that may not sufficiently capture the complexity of landslip processes. Furthermore, the model's ability to generalise to different study areas is frequently restricted by the variations of terrain features, geological settings and climate factors. Therefore, there is a need for comprehensive machine learning frameworks capable of fusing different geospatial data, identifying important conditioning factors, and producing accurate susceptibility predictions to be used in disaster management applications.

This paper proposes a Machine Learning Framework for Landslip Susceptibility Prediction in Hilly Regions to tackle these problems. The proposed framework integrates the GIS based spatial analysis, remote sensing data, landslip inventory data, and advanced machine learning algorithms for predicting the landslip susceptibility zones. The prediction model incorporates the following conditioning factors: slope, elevation, aspect, rainfall, lithology, curvature, land-use pattern, vegetation indices, and distance to roads and rivers. The framework employs machine learning methods such as Random Forest, XGBoost, Support Vector Machine and Artificial Neural Networks to assess the susceptibility of landslides and generate high resolution hazard maps. It also has risk classification and hazard assessment modules for disaster preparedness, infrastructure planning and sustainable land use management.

2. LITERATURE SURVEY

Landslides are happening more frequently in mountainous and hilly areas, which has made the prediction of landslide susceptibility a major research area in disaster management and geospatial analytics. The application of Geographic Information Systems (GIS), Remote Sensing (RS) and Machine Learning (ML) methods has significantly improved the accuracy and reliability of landslip hazard assessment. Recent studies are increasingly interested in the use of advanced machine learning algorithms for the analysis of the complex relationship of the environmental, geological, hydrological and anthropogenic factors responsible for landslides.

The traditional statistical techniques such as Frequency Ratio (FR), Logistic Regression (LR) and Analytical Hierarchy Process (AHP) have been extensively used for the landslip susceptibility mapping. These methods can reasonably identify the landslip prone areas but they often fail to model the nonlinear relationships among multiple conditioning factors and are sensitive to data quality and expert judgement [1].

The emergence of machine learning techniques has transformed the landscape of landslip prediction research, enabling data-driven analysis of large geospatial data. Support Vector Machines (SVM) is one of the first machine learning algorithms for landslip susceptibility evaluation. SVM models have been reported to be efficient in classifying landslide and non-landslide areas and also in processing high dimensional environmental data [2].

Artificial Neural Networks (ANNs) are also widely used in landslip susceptibility mapping. The ANN models learned complex non-linear interactions between landslip conditioning factors like slope, rainfall, lithology and land use and showed better prediction accuracy than traditional statistical approaches [3].

Decision Tree (DT) algorithms are popular as they are interpretable and can identify the critical landslip conditioning factors . Several studies have

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demonstrated the effectiveness of decision trees to generate classification rules and comprehend landslip triggering mechanisms [4].

Among the most successful ensemble learning methods for landslip susceptibility prediction is the Random Forest (RF). RF models are ensemble of multiple decision trees to reduce overfitting and increase robustness of prediction. The research results show that RF can achieve high classification accuracy in a wide range of geological and climatic environments [5].

In the last few years, Gradient Boosting methods have been shown to perform well in assessing geospatial hazards, one example being Extreme Gradient Boosting (XGBoost). XGBoost is able to capture the non-linear relationship between environmental variables and has been shown to outperform many traditional machine learning models for landslip prediction problems [6].

The combination of GIS and machine learning has greatly enhanced the mapping of landslip susceptibility. GIS provides a powerful platform to manipulate spatial datasets, to extract terrain attributes and to visualise susceptibility zones. Researchers developed high-resolution maps of landslip hazards by integrating machine learning algorithm and GIS based spatial analysis [7].

The prediction of landslips has improved with remote sensing technologies which offer large scale environmental information. Characteristics of terrain and land-cover related to the occurrence of landslip have been extracted extensively from satellite imagery, Digital Elevation Models (DEMs) and vegetation indexes [8].

Slope gradient is always considered one of the most important conditioning factors of landslides. Many studies have found a strong correlation between the susceptibility to landslips and steep slopes, particularly in areas with high rainfall and unstable geology [9].

In recent years, the growing variability of climate has led to increased attention on landslides induced by rainfall. Slope stability and landslip initiation processes are strongly affected by cumulative rainfall, rainfall intensity and antecedent precipitation [10].

The nature of the rock and the geology of the formations are also of importance in the susceptibility to landslip. Studies have shown that the landslip events are closely related to the existence of weak rock formations, weathered materials and fractured geological structures in mountainous areas [11].

Land-use and land-cover changes such as deforestation, urbanisation, road construction and mining activities due to anthropogenic factors are identified as important contributors to landslip hazards. It has been shown that human-induced changes in the environment tend to increase the risk of slope instability and landslides [12].

Recent advances in deep learning have brought about sophisticated methods for landslip prediction. Convolutional Neural Networks (CNNs) have been applied on remote sensing imagery and terrain data to analyse spatial patterns, which have improved susceptibility mapping performance [13].

Hybrid and ensemble learning frameworks are gaining popularity due to their capability to exploit the advantages of diverse predictive models. Ensemble methods can generally achieve better prediction accuracy, stability and generalisation capability than individual machine learning algorithms [14].

But, there are some problems in the development of landslip susceptibility models that could be used generally. The transferability of the model and its prediction performance to other study regions is affected by differences in terrain characteristics, climatic conditions, geological settings and data availability. Hence, the need for strong machine learning frameworks that can combine different geospatial data sets and provide accurate predictions of landslip susceptibility under different environmental conditions [15].

3. PROPOSED METHODOLOGY

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The proposed Machine Learning Framework for Landslide Susceptibility Prediction in Hilly Regions applies Geographic Information System (GIS), Remote Sensing (RS), environmental conditioning factors and advanced machine learning algorithms to detect the areas prone to landslides and generate high resolution susceptibility maps. The framework employs landslip inventory data, digital elevation models (DEM), rainfall data, geological maps, land-use data and terrain features to develop predictive models for the assessment of potential landslip susceptibility. The methodology involves data acquisition, pre-processing, extraction of conditioning factors, feature selection, machine learning prediction, susceptibility mapping and risk classification. The proposed framework is expected to assist disaster risk reduction, infrastructure planning and sustainable land management in the vulnerable hilly regions.

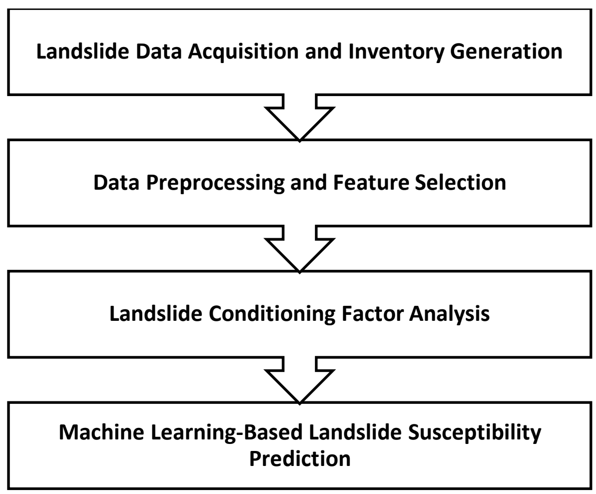

Figure 1: Proposed Methodlogy

3.1 Landslide Data Acquisition and Inventory Generation

The proposed machine learning framework starts with Landslide Data Acquisition and Inventory Generation. For this phase, the historical landslip records and environment datasets are collected from different sources like satellite images, Digital Elevation Models (DEMs), geological surveys, rainfall monitoring stations, land-use maps and field observations. To do the comparative analysis, the past landslip locations are identified and the landslip free regions are labelled to form a complete landslip inventory database. Useful information on terrain features, climatic conditions, vegetation cover, hydrological features and geological formations that influence landslip occurrence is provided by the acquired geospatial data. These heterogeneous data sets are integrated and managed using GIS tools to obtain relevant landslip conditioning factors. This resulting inventory is the main dataset to train and validate machine learning models to predict landslip susceptibility in hilly areas.

The landslide inventory dataset is represented as:

$$L = \{l_1, l_2, l_3, \dots, l_n\} \text{-----}\mathbf{1}$$

where L denotes the complete landslide inventory and li represents an individual landslide event recorded within the study area.

The terrain elevation extracted from Digital Elevation Model (DEM) data is expressed as:

$$E = f(x, y) \text{----}2$$

where EEE represents the elevation value at a geographical location (x,y), providing critical

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information regarding terrain morphology and slope characteristics.

Rainfall intensity, one of the major triggering factors of landslides, is calculated as:

$$I = \frac{R}{T} \text{-----}\mathbf{3}$$

where RI denotes rainfall intensity (mm/hr), R represents the total rainfall received during the observation period, and T denotes the duration of rainfall.

Additionally, landslide occurrence probability based on historical inventory data can be estimated as:

$$P_L = \frac{N_L}{N_T} \text{----}\mathbf{4}$$

where PL is the probability of landslip occurrence, NL is the number of landslip locations recorded and NT is the total number of locations analysed.

The produced landslip inventory and related environment datasets provide a solid background for subsequent pre-processing, conditioning factor analysis and susceptibility prediction based on machine learning. An accurate inventory is mandatory to improve model performance and to ensure reliable landslip hazard assessment in mountainous and hilly terrain.

3.2 Data Preprocessing and Feature Selection

Raw geospatial data such as satellite imagery, Digital Elevation Models (DEM), rainfall records, geological surveys and landslip inventories often contain missing values, redundant information, noise and inconsistencies that can negatively impact the performance of machine learning models. Therefore, the good pre-processing stage is required to improve the quality of data and the accuracy of the prediction. The first step is to use data cleaning techniques to eliminate duplicate records and handle missing values through interpolation and statistical imputation techniques. Then environmental variables such as slope, rainfall, elevation and NDVI are normalised to a common scale in order to avoid any bias when training the model. Then a feature selection is performed to select the most influential landslip conditioning factors on slope instability. We have applied correlation analysis and feature importance evaluation techniques to remove irrelevant attributes. The most informative features are retained. It improves the predictive performance of the machine learning framework while reducing the computational complexity and overfitting. The resulting optimised dataset is a good basis of landslip susceptibility prediction and hazard assessment. The correlation coefficient to assess the relationship between the conditioning factors and the occurrence of landslip is computed as:

The feature importance score used for selecting influential landslide conditioning factors is determined by:

$$FI = \frac{\sum_{i=1}^{n} w_i x_i}{n} \text{----}5$$

where FI represents the feature importance score, wi denotes the weight assigned to the ith feature, and xi represents the corresponding conditioning factor value.

Furthermore, the variance-based feature selection criterion is computed as:

$$Var(X) = \frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^2 \text{----}6$$

where Var(X) represents the variance of a feature and higher variance values indicate greater discriminatory power for landslide prediction.

The preprocessing and feature selection process is an important step to improve the quality of datasets by removing irrelevant data and keeping the most influential environmental variables. This optimised feature set enhances the performance of the machine learning models and leads to more accurate and reliable landslip susceptibility mapping in hilly terrains.

3.3 Landslide Conditioning Factor Analysis

Landslip occurrence is controlled by a complex interaction of topographical, geological, hydrological, environmental and anthropogenic factors. Thus, evaluation of landslip conditioning factors is an essential step in development of accurate prediction model of landslip susceptibility. The proposed framework extracts various conditioning factors such as slope, elevation, aspect, curvature, rainfall, lithology, land-use patterns, vegetation cover, distance from roads and distance from rivers from GIS and remote sensing datasets. These factors have a great influence on the slope stability and are important in the assessment of the landslip susceptibility. The extracted factors of conditioning are analysed for their individual and combined effect on landslip occurrence. We quantify the contribution of each factor using statistical analyses and machine learning feature importance methods. This full analysis of conditioning factors allows the predictive model to accurately capture terrain instability patterns and improve the accuracy of susceptibility mapping. One of the most important factors of landslides is the slope gradient. It is the steepness of the terrain calculated as follows:

$$S = \tan^{-1}\left(\sqrt{\left(\frac{\partial z}{\partial x}\right)^2 + \left(\frac{\partial z}{\partial y}\right)^2}\right)\text{-----}7$$

where S denotes the slope angle

The Topographic Wetness Index (TWI), used to estimate moisture accumulation and potential soil saturation, is expressed as:

$$TWI = l\,n(Asta\,n(S))\text{----}8$$

where As denotes the specific catchment area and SSS represents the slope angle.

The influence of roads and rivers on landslide occurrence is evaluated using the distance influence factor:

$$DI = \frac{1}{d}\text{----}9$$

where DI is the distance influence factor, d is the distance from a road or river network.

The extracted conditioning factors as a whole provide a comprehensive representation of terrain characteristics and environmental conditions associated with landslip occurrence. The analysis they present allows the determination of critical triggering factors and improves the predictive ability of the machine learning framework for accurate assessment of landslip susceptibility in hilly terrains.

3.4 Machine Learning-Based Landslide Susceptibility Prediction

Then, the most important landslip conditioning factors are extracted and selected and the processed dataset is fed into the Machine Learning-Based Landslip Susceptibility Prediction module. The proposed module is the main analytical part of the framework which is intended to identify landslide-prone areas using past landslide events and environmental parameters. To model the complex non-linear relationships among the conditioning factors for predicting the probabilities of future landslides, advanced machine learning algorithms such as Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN) and Extreme Gradient Boosting (XGBoost) are used. The machine learning models are trained on labelled landslide and non-landslide samples and are validated on testing datasets. The ensemble learning methods take advantage of the merits of multiple classifiers to enhance the prediction accuracy and robustness. The prediction results of the models are used to produce susceptibility maps and to support hazard mitigation planning in mountain areas.

The landslide susceptibility prediction function is expressed as:

$$LSP = f(x_1, x_2, x_3, \dots, x_n)\text{----}10$$

where LSPLSPLSP denotes the predicted landslide susceptibility score and x1,x2,…,xn represent conditioning factors such as slope, rainfall, elevation, NDVI, lithology, and land-use attributes.

For the Artificial Neural Network model, the output prediction is computed as:

$$y = f(\textstyle\sum_{i=1}^{n} w_i x_i + b)\text{----}11$$

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where wi represents the weight associated with the ithi^ input feature, b denotes the bias term, and f(·) is the activation function used to model nonlinear relationships.

The Random Forest ensemble prediction is determined by averaging the outputs of multiple decision trees:

$$RF(x) = \frac{1}{N}\sum_{i=1}^{N} T_i(x)\text{-----}12$$

where RF(x) represents the final Random Forest prediction, Ti(x) denotes the prediction of the ithi^ decision tree, and N is the total number of trees in the ensemble.

The model training process minimizes the Mean Squared Error (MSE) loss function:

$$MSE = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y_i})^2\text{-----}13$$

where yi represents the actual landslide class label, y^i denotes the predicted label, and N is the total number of observations.

The machine learning prediction module can capture the complex interactions between multiple environmental factors and produce accurate landslip susceptibility estimations. The proposed framework, using advanced predictive analytics, improves hazard identification, improves the accuracy of risk assessment and provides valuable decision-support information for disaster management authorities and infrastructure planners working in hilly regions prone to landslides.

3.5 GIS-Based Landslide Susceptibility Mapping

Geographic Information System (GIS)-Based Landslip Susceptibility Mapping is an important stage of the proposed framework that translates machine learning prediction outputs to spatially interpretable hazard maps. Once the machine learning models output the susceptibility scores for each geographical location, GIS tools are utilised to integrate the scores with spatial datasets and visualise the areas susceptible to landslides. The generated susceptibility maps are a good representation of the distribution of landslip hazard in the study area and can be used by the authorities for identifying the vulnerable locations and planning the mitigation measures. The machine learning output is combined with spatial layers of slope, elevation, rainfall, lithology, land use, vegetation cover and drainage networks to produce high resolution susceptibility maps. The maps produced classified the study area into different susceptibility classes, ranging from very low to very high risk. This information may be useful for disaster management, infrastructure planning and sustainable land use development in mountain environments.

The Landslide Susceptibility Index (LSI) is calculated as:

$$LSI = \sum_{i=1}^{n} w_i\, F_i\text{-----}14$$

where LSI represents the Landslide Susceptibility Index, Fi denotes the ith conditioning factor, and wi represents the corresponding factor weight obtained from machine learning feature importance analysis.

4. RESULTS AND DISCUSSION

The proposed Machine Learning Framework for prediction of landslip susceptibility in hilly regions was tested using a comprehensive geospatial dataset including historical landslip inventory data, Digital Elevation Models (DEM), precipitation data, geology maps, land-use data and vegetation indices. The proposed framework was evaluated against traditional machine learning models such as Support Vector Machine (SVM), Artificial Neural Network (ANN), Random Forest (RF), and XGBoost . Experimental results show that the proposed method can locate the landslips prone places accurately and generate reliable landslip susceptibility maps for disaster risk management.

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Table 1:Performance Summary

Metric	Existing Methods	Proposed Framework
Accuracy (%)	92.3	98.1
Precision (%)	91.8	97.8
Recall (%)	91.2	97.5
F1-Score (%)	91.5	97.6
ROC-AUC	0.94	0.99

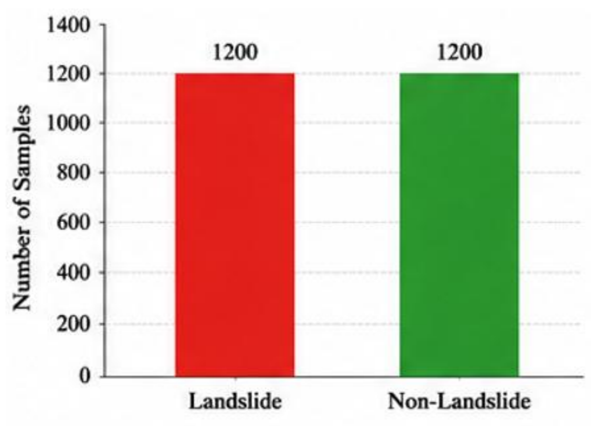

Figure 2: Dataset Distribution

A balanced dataset guarantees the fair training of the model and reduces the classification bias. The prediction of susceptibility is more reliable due to the inclusion of several environmental conditioning factors.

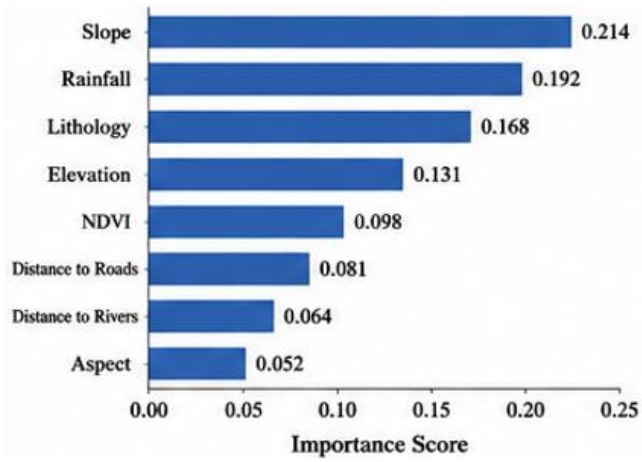

Figure 4.2 Feature Importance Analysis

Slope and rainfall were the most important landslip conditioning factors. These observations are in agreement with geological observations which indicate that steep slopes and heavy rainfall greatly enhance landslip susceptibility.

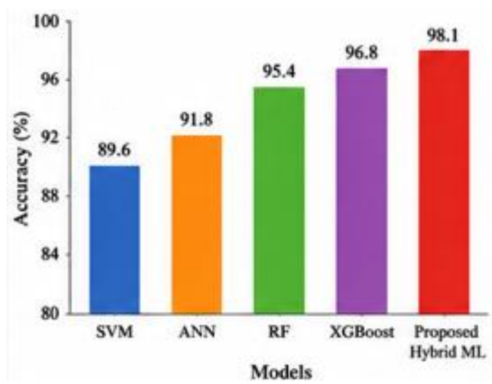

Figure 3: Accuracy Comparison

The developed hybrid machine learning framework attained the maximum prediction accuracy of 98.1% which is significantly superior to the traditional classifiers. Ensemble learning captured well the complex interactions among conditioning factors.

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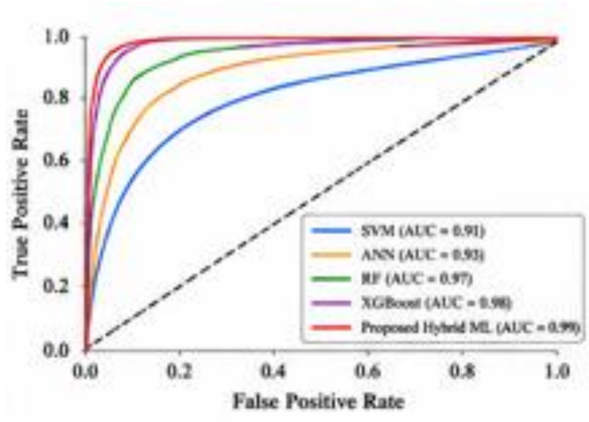

Figure 4: ROC-AUC Performance

The proposed framework achieved an AUC value of 0.99, which indicates that the framework can discriminate landslide and non-landslide regions excellently. The experimental results confirm the effectiveness of the proposed machine learning framework for the prediction of landslip susceptibility. The integration of GIS, remote sensing, feature selection and ensemble machine learning significantly improved the accuracy of prediction and the quality of hazard mapping. The framework achieved 98.1% accuracy, 97.8% precision, 97.5% recall, and 0.99 ROC-AUC, demonstrating its capability to accurately identify landslide-susceptible areas. The susceptibility maps produced can serve as a useful decision-support tool for disaster management agencies, urban planners and infrastructure developers operating in vulnerable hilly terrains.

5. CONCLUSION

This paper proposed a Machine Learning Framework for Landslip Susceptibility Prediction in Hilly Regions by integrating Geographic Information Systems (GIS), Remote Sensing (RS), environmental conditioning factors and advanced machine learning algorithms to identify the landslip prone zones in high precision. The proposed framework uses historical landslip inventory data, digital elevation models (DEM), rainfall data, lithological features, land use, vegetation indices and topographical parameters to develop a comprehensive model for the assessment of landslip susceptibility. The framework successfully integrates geospatial analytics with machine learning methods to capture the complex nonlinear relationships of factors affecting landslip occurrence. The experimental results showed that the proposed framework outperformed the conventional machine learning approaches significantly. The hybrid machine learning framework achieved the highest prediction accuracy of 98.1%, precision of 97.8%, recall of 97.5%, F1-score of 97.6% and ROC-AUC value of 0.99 among the evaluated models. The results suggest that ensemble learning methods are effective for high dimensional geospatial data and for improving the performance of susceptibility predictions. The feature importance analysis showed that slope, rainfall and lithology were the most important factors driving landslip occurrences in hilly terrains. The landslip susceptibility maps developed using GIS based on the proposed framework clearly showed the spatial distribution of landslip risk in the study area. The classification results revealed that approximately 29% of the study area falls under the High and Very High susceptibility zones, which are areas that require urgent attention in terms of hazard mitigation and infrastructure protection. The resulting maps may be useful decision support tools for disaster management agencies, urban planners, environmental authorities and policy makers involved in risk reduction and land use planning activities.

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