Prediction of Landslides Using Extracted Environmental and Topographic Features from Multispectral Satellite Images

Chethana Vasudevaiah
B.M.S. College of Engineering, Bull Temple Road, Bengaluru -560019, Karnataka, India | Dayananda Sagar College of Engineering, Bangalore-560111, Karnataka, India | Visvesvaraya Technological University, Belagavi-590018, Karnataka, India
chethanav499@gmail.com (corresponding author)

Rashmi Shivaswamy
School of Computer Science and Engineering, RV University, Bangalore-560059, Karnataka, India
rashmineha.s@gmail.com

Rajeshwari Janthakal
Dayananda Sagar College of Engineering, Bangalore-560111, Karnataka, India | Visvesvaraya Technological University, Belagavi-590018, Karnataka, India
rajeshwarij-ise@dayanandasagar.edu

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ABSTRACT

Landslides are natural disasters that lead to the loss of lives and economic damage in a particular location. In India, particularly in hilly areas, landslides occur owing to factors such as rainfall, vegetation changes, changes in atmospheric conditions, and topographic features. The occurrence of landslides disrupts transportation, destroys infrastructure, and blocks roads for people near the location. Using satellite images, environmental and topographic features such as aspect, slope, curvature, contour, rainfall, soil moisture, atmospheric changes, and variations in vegetation index values can be extracted. These extracted features were used for landslide prediction, and the newly labeled dataset, comprising 1,738 landslides and 1,598 randomly generated non-landslide locations in India, was used for our experiment. Some previous studies considered either topographic or environmental features, whereas others used small datasets. In this work, both environmental and topographic features of all these locations were extracted from multispectral Landsat satellite images. A new dataset with features such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Normalized Difference Built-up Index (NDBI), slope, aspect, elevation, and precipitation was prepared. Using this dataset, Artificial Intelligence (AI) models were built utilizing various Machine Learning (ML) algorithms, such as the Light Gradient Boosting Machine (LightGBM), Random Forest (RF), CatBoost, and Multilayer Perceptron (MLP) neural network models, to predict landslides. These models were assessed using confusion matrices, accuracy, Receiver Operating Characteristic (ROC) curves, and comparative metrics. RF, LightGBM, and CatBoost achieved the highest accuracy of 96%, and the MLP achieved an accuracy of 93%. The ROC–Area Under the Curve (ROC–AUC) score was 0.86 for the LightGBM model, which was the highest compared to the other three models. This work used multispectral satellite images and advanced ML models for reliable landslide predictions in India.

Keywords-landslide; Machine Learning (ML); Random Forest (RF); Light Gradient Boosting Machine (LightGBM); CatBoost; Multilayer Perceptron (MLP) neural network; topographic features

I. INTRODUCTION

Landslides are a frequent hazard in several regions of India due to the country's diverse topographical characteristics, particularly in the Western Ghats, the Himalayan belt, and major river basin regions. These events result in significant loss of life, damage to infrastructure, and economic losses. Increasing anthropogenic pressure, deforestation, and continuous variations in rainfall, temperature, and terrain morphology contribute to the rising unpredictability of landslides. Consequently, accurate and scalable landslide prediction models are essential for disaster risk reduction and effective mitigation planning.

Traditional landslide assessment approaches depend heavily on geological surveys and historical inventories, which are time-consuming, labor-intensive, and spatially limited. Advances in remote sensing technologies now enable the use of high-resolution multispectral and Synthetic Aperture Radar (SAR) satellite imagery from missions such as Landsat, Sentinel, Cartosat, and ResourceSat. These datasets support the extraction of critical environmental and topographic variables—rainfall, vegetation cover, soil moisture, slope, aspect, elevation, and curvature—which are essential for modeling landslide susceptibility. Recent global satellite missions, including those launched by the United States, Russia, China, and India, facilitate pixel-, object-, and feature-level data fusion, high-frequency displacement monitoring, and the development of benchmark geospatial datasets, thereby strengthening Artificial Intelligence (AI)-driven geohazard analysis.

Driven by these advancements, modern research increasingly combines multispectral indices (Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Normalized Difference Built-up Index (NDBI)), rainfall, temperature, and soil moisture with Digital Elevation Model (DEM)-derived features to build robust landslide prediction models. In this context, various studies have adopted Machine Learning (ML) and Deep Learning (DL) approaches to leverage the integration of remotely sensed environmental and topographic parameters. Authors in [1] offer a comprehensive review highlighting the effectiveness of supervised ML methods—including decision trees, Support Vector Machines (SVMs), Bayesian models, fuzzy logic, and neural networks—with reported accuracies ranging from 62% to 99% depending on data availability and methodology. Complementing this, authors in [2] document the transition from classical ML to deep neural networks for landslide detection, noting persistent challenges in class imbalance, small-object detection, and cross-region generalization due to limited datasets.

Several studies have explored hybrid or multi-source data integration for landslide modeling. Authors in [3] integrate rainfall, slope, and vegetation indices extracted from satellite data into an AI-based landslide prediction framework, employing Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (BiLSTM) models for rainfall forecasting. Authors in [4] demonstrate the value of integrating multiple geospatial datasets with ML algorithms such as Random Forest (RF), XGBoost, k-Nearest Neighbors (KNN), and SVM, emphasizing the importance of feature selection and addressing data imbalance to improve prediction robustness. Similarly, authors in [5] apply Artificial Neural Networks (ANNs) using remote sensing inputs to deliver real-time landslide prediction capabilities, particularly for western India.

DL models have gained prominence due to their capacity to automatically extract spatial and temporal patterns from complex geospatial data. Authors in [6] propose a Hybrid Convolutional Neural Network (HCNN) architecture that achieves high accuracy and overcomes several limitations of traditional ML by extracting multi-scale spatial features from high-resolution imagery. Authors in [7] extend this approach by combining CNN and LSTM networks to jointly model spatial and temporal patterns of landslide occurrences. Fuzzy logic has also been utilized, as shown by authors in [8], who generate continuous-valued susceptibility maps from environmental factors including rainfall, slope, aspect, curvature, drainage distance, land use/land cover, and geomorphology.

Additional DL advancements include Convolutional Neural Network (CNN)-based feature extraction from satellite images, as presented by authors in [9], and 3D CNNs for processing pre- and post-event Sentinel-2 imagery, as developed by authors in [10], which capture both spatial and temporal components of landslide events. Authors in [11] enhance U-Net CNN architectures with multispectral images and DEMs for improved landslide segmentation in complex terrains. Hybrid models have also shown promise, such as the SlideSense framework introduced by authors in [12], which combines CNN-derived spatial features with RF classifiers for environmental variables, outperforming classical ML methods.

Novel hybrid frameworks continue to refine landslide prediction, such as the integration of DInSAR and U-Net models by authors in [13], and the combination of Vision Transformers with traditional image processing for flood and landslide prediction proposed by authors in [14]. Additionally, authors in [15] integrate DeepLabV3+ semantic segmentation with GIS-based Multicriteria Decision Making (MCDM) using high-resolution topographical and environmental variables, achieving superior performance in fine-scale susceptibility mapping. Ensemble DL approaches have also been explored, such as the framework proposed by authors in [16], which integrates spectral, texture, and terrain features from Sentinel-2 and ALOS DEM to enhance landslide detection accuracy in complex terrains. Enhanced CNN–LSTM combinations by authors in [17] further demonstrate the growing effectiveness of hybrid DL systems.

Together, these studies highlight the expanding role of remote sensing and AI techniques in landslide prediction, emphasizing the significance of integrating multisource datasets, addressing class imbalance, improving generalization, and leveraging DL for spatial–temporal feature extraction. Building on this foundation, the present work combines multispectral indices, rainfall, soil moisture, and DEM-derived topographic features to develop ML models such as RF, Light Gradient Boosting Machine (LightGBM), CatBoost, and Multilayer Perceptron (MLP) for predicting landslides across India, contributing to scalable and data-driven geohazard risk assessment.

II. METHODOLOGY

A. System Architecture

Figure 1 illustrates the system architecture integrating data acquisition, feature extraction, and ML processes for landslide prediction.

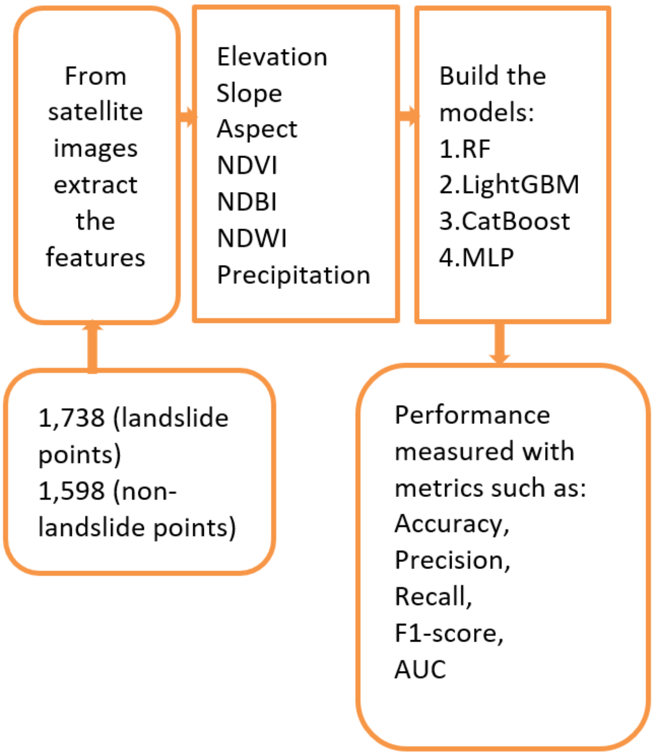


Fig. 1. System architecture of the proposed landslide prediction framework.

B. Proposed Machine Learning Models

This section elaborates on the mathematical algorithms, workings, and equations for each ML model applied in this study—RF, LightGBM, CatBoost, and MLP neural network—for landslide susceptibility prediction. The focus was on how each model processed the input features NDVI, NDWI, NDBI, elevation, slope, aspect, and precipitation to predict landslide risk

1) Random Forest

RF is an ensemble learning method that builds a collection (forest) of decision trees during training. Each tree is trained on a random subset of data (with replacement—bootstrap sampling), and random subsets of features are considered at each split. The final prediction is made by majority vote (classification) or averaged (regression) across all trees.

The core equations are as follows:

- Tree construction: Each tree T_k makes a prediction $f_k(\vec{x})$ for input vector $\vec{x}$.
- Aggregation:

$$\hat{y} = \mathrm{mode}(f_1(\vec{x}), f_2(\vec{x}), \dots, f_n(\vec{x})) \quad (1)$$

where n is the number of trees.

- Decision node splitting (Gini impurity for classification):

$$\mathrm{Gini}(t) = 1 - \sum_{c=1}^{C} [p(c|t)]^2 \quad (2)$$

where $p(c|t)$ is the proportion of class c at node t.

2) Light Gradient Boosting Machine

LightGBM is a gradient boosting framework using tree-based learning algorithms. It builds new trees sequentially; each aimed at correcting the errors (residuals) from the previous trees. LightGBM employs leaf-wise tree growth, histogram-based feature binning, and other optimizations for speed and memory efficiency.

The core equations are as follows:

- Ensemble output:

$$F_M(\vec{x}) = \sum_{m=1}^{M} f_m(\vec{x}) \quad (3)$$

where f_m is the prediction of the m-th tree.

- Objective (log-loss for binary classification):

$$L = \sum_{i=1}^{N} l(y_i, \hat{y}_i) + \Omega(f) \quad (4)$$

where l is the loss function (e.g., log-loss), y_i and $\hat{y}_i$ are true and predicted labels, and $\Omega(f)$ is the regularization term controlling model complexity.

- Update rule: At boosting step m:

$$g_i = \frac{\partial l(y_i, F_{m-1}(\vec{x}_i))}{\partial F_{m-1}(\vec{x}_i)}, h_i = \frac{\partial^2 l(y_i, F_{m-1}(\vec{x}_i))}{\partial F_{m-1}(\vec{x}_i)^2} \quad (5)$$

where g_i and h_i are the first and second derivatives (gradients and Hessians) of the loss with respect to the prediction.

3) CatBoost

CatBoost is a gradient boosting algorithm optimized for datasets with categorical features, introducing ordered boosting and symmetric (oblivious) trees. CatBoost processes categorical data natively without explicit encoding, reducing overfitting and improving generalization—ideal for smaller or imbalanced datasets.

The core equations are as follows:

- Prediction update:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + \eta \cdot f_t(\vec{x}_i) \quad (6)$$

where η is the learning rate and f_t is the new tree at iteration t.

- Loss function (log-loss for binary):

$$L = -\sum_{i=1}^{N} [y_i \log \sigma(\hat{y}_i) + (1 - y_i) \log(1 - \sigma(\hat{y}_i))] \quad (7)$$

where $\sigma(\hat{y}_i)$ is the sigmoid activation.

- Ordered boosting: For each data point, CatBoost computes the target statistics for a categorical feature using only samples that come before that point in ordered data, reducing target leakage.

4) Multilayer Perceptron

MLP is a feed-forward neural network consisting of input, hidden, and output layers. Each layer computes a weighted sum of inputs, applies a non-linear activation function, and passes results to the next layer.

The core equations are as follows:

- Layer output:

$$a_j^{(l)} = \sigma\left(\sum_i w_{ji}^{(l)} a_i^{(l-1)} + b_j^{(l)}\right) \quad (8)$$

where $a_j^{(l)}$ is the activation of unit j in layer l, $w_{ji}^{(l)}$ is the weight between layer $l-1$ and l, $b_j^{(l)}$ is the bias term, and σ is the activation function (e.g., ReLU, sigmoid).

- Output layer for binary classification:

$$\hat{y}_i = \sigma\left(\sum_j w_j a_j^{(L)} + b\right) \quad (9)$$

where $\sigma(x) = \frac{1}{1+e^{-x}}$.

- Loss function (binary cross-entropy):

$$L = -\sum_{i=1}^{N}[y_i \log \hat{y}_i + (1-y_i)\log(1-\hat{y}_i)] \quad (10)$$

- Training (backpropagation):

$$w_{ij} \leftarrow w_{ij} - \alpha \frac{\partial L}{\partial w_{ij}} \quad (11)$$

where α is the learning rate.

III. EXPERIMENTAL WORK

A. Dataset Preparation

Landslides occur only in specific locations across India. The longitude and latitude of these locations are available from NASA's Global Landslide Catalog (GLC) (https://gpm.nasa.gov/landslides/data.htm) [18]. Landsat satellite images for these locations were used to extract features such as slope, aspect, and elevation. Since Landsat images are multispectral, they provide various bands, making it possible to calculate the NDBI, NDVI, and NDWI. Precipitation data were obtained from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) dataset [19].

The features extracted for landslide locations were labeled as 1, whereas non-landslide data points were randomly selected, and the same features were extracted and labeled as 0. In our study, we used 1,738 landslide locations and 1,598 non-landslide locations and extracted the corresponding features. A Comma-Separated Values (CSV) file was created containing all features: elevation, slope, aspect, NDVI, NDBI, NDWI, and precipitation, with the last column representing the label (0 for non-landslide and 1 for landslide).

B. Implementation

The prepared new labeled dataset for both landslide and non-landslide locations, consisting of a total of 3,336 locations in India, was used as input for the ML models. The dataset was split into 80% for training and 20% for testing.

The implementation steps are as follows:

1. Data preprocessing: Handled missing values and normalized feature values where necessary; encoded target variables using binary encoding (0 = non-landslide, 1 = landslide).
2. Data splitting: Utilized train_test_split from scikit-learn with stratification on the target label.
3. Model training:
   - RF: Used default settings with 100 estimators.
   - LightGBM: Configured with a binary classification objective; automatically tuned the number of iterations and learning rate.
   - CatBoost: Enabled categorical feature support and used internal early stopping.
   - MLP: Configured with a single hidden layer and ReLU activation.
4. Model evaluation:
   - Predictions on the test set were generated for each model.
   - Calculated classification metrics and constructed confusion matrices.
   - Computed the Receiver Operating Characteristic–Area Under the Curve (ROC–AUC) to measure model discrimination capacity.

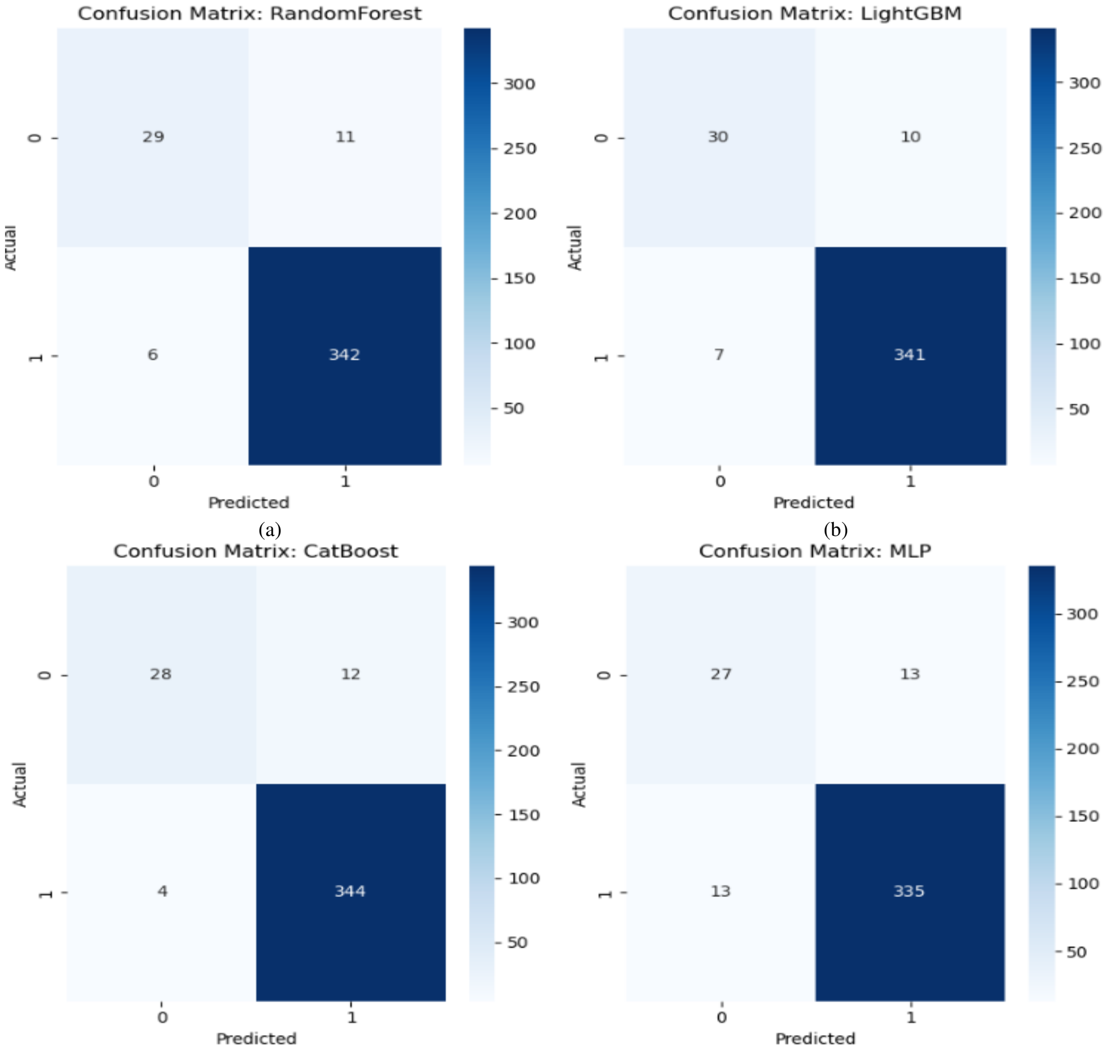
IV. RESULTS AND DISCUSSION

Figure 2 presents the implementation results with confusion matrices, whereas Figure 3 displays the ROC curves of the ML models post-implementation. As illustrated in Figure 4, all four algorithms—RF, LightGBM, CatBoost, and MLP—demonstrated high overall accuracy (≥93%) and strong classification performance on the test set.

The tree-based ensemble methods (RF, LightGBM, and CatBoost) consistently outperformed the MLP neural network, especially in identifying the minority class (non-landslide). LightGBM achieved the highest ROC–AUC (0.865), indicating superior overall class discrimination, whereas CatBoost attained the highest precision for the minority class (0.88), effectively reducing false positives. RF demonstrated reliable and balanced performance, maintaining consistent recall and precision for both classes. Conversely, the MLP neural network, although generally proficient in detecting landslides, faced challenges with accurately predicting the minority class, likely due to its sensitivity to class imbalance and the limited representation of non-landslide samples in the dataset.

A. Model Comparison

The performance of all four models was compared using standard classification metrics. RF and LightGBM achieved nearly identical results, with accuracy, precision, recall, F1-score, and ROC–AUC values ranging from 0.95 to 0.98, demonstrating balanced and reliable performance across both classes. CatBoost slightly outperformed the other models in recall and F1-score, indicating a strong ability to correctly identify landslides. The MLP neural network, although effective in detecting landslides, exhibited a lower AUC and slightly reduced values across several metrics for the minority class, likely due to its sensitivity to class imbalance.



(a) (b) (c) (d)

Fig. 2. Confusion matrices of the ML models: (a) RF, (b) LightGBM, (c) CatBoost, (d) MLP.

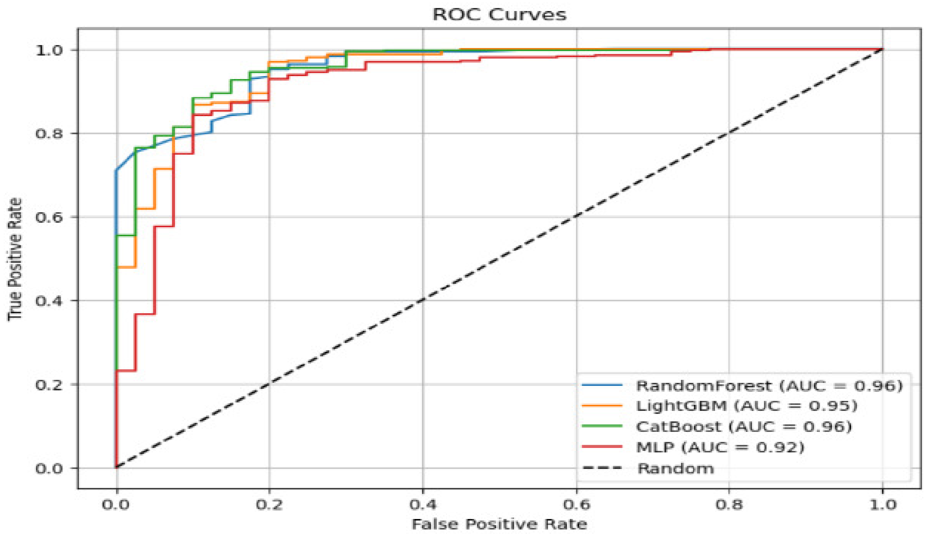


Fig. 3. ROC curves of the ML models.

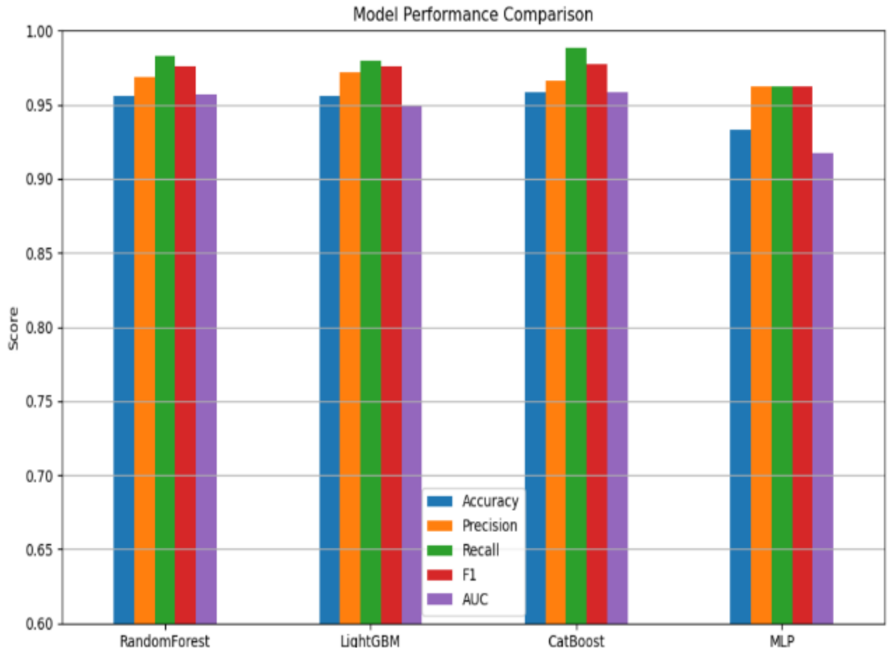


Fig. 4. Performance comparison of the ML models.

These results indicate that tree-based ensemble models are more suitable for landslide susceptibility mapping in imbalanced real-world datasets, offering high sensitivity, specificity, and discrimination capability. Practically, the choice between LightGBM and CatBoost may depend on application needs, whether prioritizing maximum landslide detection (high recall) or minimizing false alarms (high precision in non-landslide cases).

Finally, these results align with findings from previous studies, which report that boosting-based algorithms such as XGBoost, CatBoost, and RF outperform neural-network-based models for landslide prediction, particularly when datasets are noisy or imbalanced. This confirms that decision-tree ensembles remain competitive and often superior for geospatial hazard prediction tasks.

V. CONCLUSION

The Machine Learning (ML) models proposed in this study—Random Forest (RF), Light Gradient Boosting Machine (LightGBM), CatBoost, and Multilayer Perceptron (MLP) neural network—exhibit strong predictive ability for assessing landslide susceptibility. These models incorporate a wide array of features, including dynamic variables such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), Normalized Difference Water Index (NDWI), and precipitation data from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS), as well as static topographic parameters such as slope, aspect, and elevation. Unlike traditional methods that depend solely on either environmental indices or terrain attributes, this framework merges multispectral, topographic, and temporal features, allowing for a more comprehensive and robust identification of areas prone to landslides. A significant innovation of this research is the combination of large-scale multispectral satellite-derived indices with high-resolution precipitation (CHIRPS) and terrain variables, utilizing over 3,000 data points from various regions in India. This extensive and diverse dataset enhances the models' ability to generalize, making the results applicable across different physiographic zones. Additionally, the comparative analysis of the four advanced ML techniques offers valuable insights into model performance under highly imbalanced landslide data conditions. The experimental findings reveal strong performance, with Area Under the Curve (AUC) values of 0.96 for RF, 0.95 for LightGBM, 0.96 for CatBoost, and 0.92 for the MLP neural network. These high AUC scores demonstrate that integrating dynamic and static features significantly boosts the models' discriminative power.

The study's contributions include: demonstrating the effectiveness of feature integration for landslide prediction, providing a comparative analysis of state-of-the-art ML models, and delivering a scalable framework that can be adapted for regional or national-scale landslide susceptibility mapping. Overall, the results highlight the potential of combining multispectral satellite data, precipitation information, and terrain attributes to develop accurate, reliable, and scalable landslide prediction models for India.

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