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Landslide Early Warning System using SAR Data and Machine Learning

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Abstract - **Landslides continue to pose a significant threat to human lives, infrastructure, transportation networks, and ecological systems, particularly in mountainous and high-rainfall regions. Recent advances in artificial intelligence, remote sensing, and geospatial analytics have transformed conventional landslide monitoring into intelligent early warning systems capable of continuous environmental assessment and rapid decision-making. This survey presents a comprehensive review of machine learning-based landslide early warning systems with particular emphasis on the integration of Sentinel-1 Interferometric Synthetic Aperture Radar (InSAR), geo-fencing, meteorological information, ensemble learning, and real-time alert dissemination. The survey consolidates the methodologies, datasets, feature engineering strategies, prediction algorithms, deployment architectures, and evaluation metrics reported in recent literature while analyzing their strengths and limitations. Furthermore, the survey presents the LandSense framework as an integrated case study demonstrating how machine learning, satellite-derived deformation monitoring, rainfall analysis, secure backend services, geospatial risk mapping, evacuation route planning, and multi-channel alert mechanisms can be combined into a unified disaster management platform. Comparative analysis of Random Forest, XGBoost, ensemble learning, deep learning, and time-series forecasting techniques highlights current research trends and identifies remaining challenges related to data availability, computational complexity, model generalization, explainability, and operational deployment. The survey concludes by outlining future research directions involving explainable artificial intelligence, transformer architectures, graph neural networks, digital twins, federated learning, and edge-based disaster intelligence for next-generation landslide early warning systems.**

Keywords - Landslide Early Warning System, Machine Learning, Random Forest, XGBoost, InSAR, Sentinel-1, Geo-Fencing, Disaster Management, Remote Sensing, Ensemble Learning, Artificial Intelligence.

I. INTRODUCTION

Landslides are among the most destructive natural hazards, causing significant loss of life, infrastructure damage, and environmental degradation worldwide. Their occurrence is influenced by multiple factors such as intense rainfall, slope instability, soil moisture, geological

conditions, and human activities. Traditional landslide monitoring methods mainly rely

on manual field surveys and rainfall threshold analysis, which often suffer from limited spatial coverage, delayed response, and insufficient predictive capability. Recent advances in Machine Learning (ML), Remote Sensing, Geographic Information Systems (GIS), and Interferometric Synthetic Aperture Radar (InSAR) have enabled the development of intelligent Landslide Early Warning Systems (LEWS) capable of providing accurate and real-time risk assessment.

This survey reviews recent developments in AI-driven landslide prediction techniques and analyzes the integration of machine learning algorithms, Sentinel-1 InSAR, geo-fencing, rainfall monitoring, and emergency alert systems for disaster management. It also presents the **LandSense** framework as a comprehensive case study that combines ensemble learning, geospatial analysis, real-time monitoring, safe route planning, and multi-channel alert dissemination into a unified early warning platform. By comparing existing approaches and identifying current research gaps, this survey highlights future directions for developing scalable, explainable, and intelligent landslide early warning systems.

Typical indicators of landslide susceptibility include:

- High rainfall intensity and prolonged precipitation.
- Ground deformation detected using Sentinel-1 InSAR.
- Steep terrain slope and unstable geological conditions.
- Increased soil moisture reducing slope stability.
- Historical landslide occurrences and hazard-prone zones.
- Surface displacement trends and deformation velocity.

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II. RELATED WORK

Li et al. [1] proposed an automated time-series InSAR framework for monitoring active landslides using Sentinel-1A satellite data. Their method combined DBSCAN clustering, deformation analysis, and the Inverse Velocity Method to predict landslide failure. The framework successfully predicted the Xinmo landslide 2–3 days before its occurrence, improving early warning capabilities.

Rajesh et al. [2] developed a hybrid machine learning and edge computing system for real-time landslide detection. The framework used multiple environmental sensors connected to a Raspberry Pi, where a Random Forest classifier processed the sensor data locally. The system generated instant alerts through IoT technology, reducing communication delays. It is suitable for remote and disaster-prone regions due to its low cost and scalability. However, it mainly relies on sensor deployment and cannot monitor large geographical areas

Gajardo et al. [3] proposed a landslide detection framework by combining Sentinel-1 SAR, Sentinel-2 optical imagery, and topographic information. The study evaluated several machine learning algorithms, including Random Forest, SVM, CART, and Gradient Tree Boosting. Among them, Random Forest achieved the highest detection accuracy. The framework also produced probability maps for post-disaster assessment. However, cloud cover and image quality affected the performance of the optical datasets.

Valli Suseela et al. [4] presented a Random Forest-based landslide detection system using environmental parameters obtained from Google Earth Engine. The model considered rainfall, slope, elevation, NDVI, and soil moisture for prediction. GPS and ESP8266 modules were integrated to provide location-based early warnings to users entering hazardous zones. The proposed system was cost-effective and suitable for disaster-prone regions. However, its prediction accuracy depends on historical environmental data.

Magudeeshwari et al. [5] designed a real-time landslide detection and alerting system using soil moisture and MEMS sensors. Sensor readings were processed by an ATmega328P microcontroller to identify abnormal ground conditions. A GSM module was used to send SMS alerts to nearby residents and authorities during emergencies. The system offered a reliable and low-cost early warning solution powered by solar energy. However, it uses threshold-based detection instead of advanced predictive machine learning models.

Chitteti et al. [6] proposed an integrated machine learning framework for flood and landslide prediction using a dataset containing 38,389 records and 21 environmental features. The framework employed classification algorithms such as Logistic Regression, SVM, Random Forest, and Decision Trees, along with regression models including XGBoost and Gradient Boosting. Experimental results showed that Logistic Regression and SVM achieved over 92% classification accuracy. The proposed system improved disaster prediction by combining multiple machine learning techniques and extensive feature engineering.

Surekha et al. [7] presented a deep learning approach for detecting landslides and floods using the Flood.csv and Global Landslide Catalog (GLC) datasets. The study compared conventional machine learning models such as Naïve Bayes, SVM, Logistic Regression, and Random Forest with deep learning models. Experimental results showed that the RNN model outperformed the traditional methods in prediction accuracy. The proposed framework demonstrated the effectiveness of deep learning for early disaster prediction.

Khalili et al. [8] proposed an advanced machine learning framework for landslide prediction using environmental and InSAR data collected from Moio della Civitella, Italy. The framework integrated Self-Supervised Learning, LSTM, Ensemble Learning, and Gradient Boosting to analyze temporal and seasonal landslide patterns. The proposed model improved prediction accuracy and supported early warning systems through anomaly detection and feature importance analysis. However, its performance depends on the quality of the available environmental data.

Kour et al. [9] developed a remote sensing-based landslide detection framework using the U-Net deep learning model. The study utilized satellite imagery to automatically segment landslide-affected regions and compared U-Net with conventional machine learning methods such as SVM and Random Forest. Experimental results indicated that U-Net achieved superior precision, recall, and F1-score for landslide detection. The proposed model demonstrated the effectiveness of deep learning for large-scale landslide mapping.

Chandra and Vaidya [10] proposed a satellite-based landslide detection framework using the EfficientDet deep learning model. The study evaluated EfficientDet variants (D0–D4) on the Bijie landslide dataset to identify landslide events from satellite images. Among the evaluated models, EfficientDet-D3 achieved the best performance with an AP@0.50 score of 0.80. The proposed framework demonstrated that deep learning can effectively improve satellite-based landslide detection and disaster management.

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I. PROPOSED SYSTEM

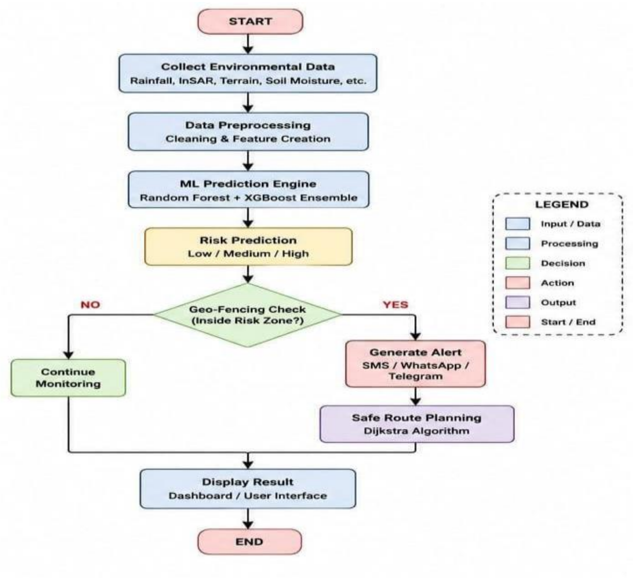

Fig 3.1 The Proposed System

Figure 3.1 outlines the workflow of the proposed system. The proposed system is a comprehensive machine learning-based landslide prediction and warning framework. It is used to predict landslide-prone areas accurately while also warning affected regions to minimize damage as much as possible. Sentinel-1 SAR, InSAR images, and other environmental data sets such as rain, soil moisture, elevation, slope, and Digital Elevation Model (DEM) will be used to make these predictions. This system's primary purpose is to predict landslides based on environmental factors such as rainfall, slope, and elevation, among others, and warn the relevant authorities to take appropriate actions before it strikes their regions. Data collection begins with the preprocessing and cleaning of the data. This involves removing unnecessary data, dealing with missing data and outliers in the data set, and normalizing the relevant features. After this step, feature engineering will be done to obtain useful features to improve the learning process of the machine learning models used. With the preprocessed and engineered data set, a prediction model will be developed using an ensemble method of extreme gradient boosting and random forest machine learning algorithms. The extreme gradient boosting algorithm is perfect for this task due to its ability to handle non-linear relationships between environmental factors and predict with high accuracy. On the other hand, ensemble random forests are known to reduce variance in data while also capturing non-linear relationships between variables. By combining both algorithms into one prediction model, the variance in the data set will be reduced, and prediction accuracy will be improved when compared to other machine learning algorithms. Furthermore, the predicted values will be used to classify each region into Low, Medium, and High-risk areas based on some thresholds. This will ensure that only the relevant authorities in each region are notified promptly.

In addition to the prediction model, the proposed system will have multiple modules attached to it for it to be effective. First, the geo-fencing module will constantly monitor whether any of the users are in a high-risk area and notify them accordingly. Secondly, the InSAR monitoring module will continuously monitor ground deformation and displacement data to track possible movements of the land. Another module that the proposed system will have is the Dijkstra routing module, which will find alternative safe routes while avoiding high-risk areas in case any of the users are in case any of the users is in a dangerous zone. All the functionalities of the system are handled by a fast API backend server. The prediction results, user authentication, database functions, and other processes are handled and controlled by the backend. A web dashboard and mobile application will display the results of the predicted landslides in each region while also displaying the monitoring results and warning notifications. SMS, WhatsApp, Telegram, and dashboard alerts will be used to send out warnings to the relevant authorities in each region, minimizing the time it would take to inform them through traditional means. Therefore, the proposed system will utilize satellite imagery from Sentinel-1 SAR and InSAR while also incorporating factors such as rain, slope, and elevation to predict landslides with high accuracy. In addition to prediction, modules such as geo-fencing, monitoring, alternative routing, and alert systems will be used to ensure that landslides cause minimal damage to both people and infrastructure.

II. SYSTEM ARCHITECTURE

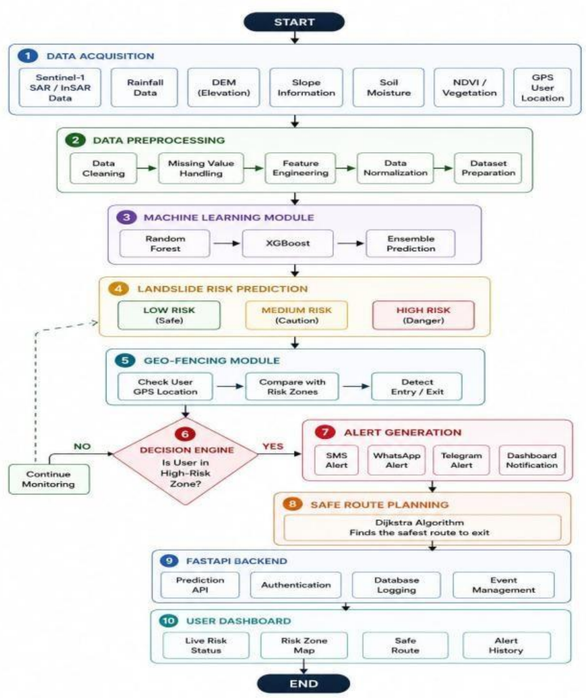

Fig 4.1 System Architecture

Figure 4.1 illustrates the overall system architecture of the proposed landslide prediction and alert system. The architecture is divided into the following modules:

- **Data Acquisition Layer:** The Data Acquisition Layer acquires environmental and geo-spatial data including Sentinel-1 SAR/InSAR, rainfall, DEM, slope, soil moisture, NDVI, and GPS coordinates. This information layer serves as an input data source for landslide susceptibility analysis.

- **Data Preprocessing Layer:** This layer involves conducting data preprocessing steps such as cleaning, filling missing values, feature engineering, data transformation, and preparation for model training in the machine learning module.

- **Machine Learning (ML) Module:** The ML module undertakes modeling functions, including Random Forest and XGBoost algorithms. These two algorithms have been considered for this study due to their high-performance capabilities in similar problems. This layer combines prediction results using these two algorithms to produce the final prediction scores.

- **Landslide Risk Prediction Layer:** This layer uses the combined prediction scores to classify the study area into Low, Medium, and High based on the predicted risk.

- **Geo-Fencing Module:** The geo-fencing module monitors the GPS location of the users and compares it with the location of the firmed high-risk zones to prompt context-aware notifications.

- **Decision Engine:** The decision engine evaluates information from the prediction and geo-fencing modules to make decisions regarding the activation of the alert notification system.

- **Alert Generation Module:** This module triggers emergency alerts via SMS, WhatsApp, Telegram, and dashboard messages to all registered users in the system upon activation.

- **Safe Route Planning Module:** The safe route planning module uses Dijkstraâ€™s algorithm to generate safe evacuation routes for users who activate emergency alerts.

- **FastAPI Back End:** The FastAPI back-end provides an interface for API prediction, authentication, database logging, and alert notification. This component connects all other components and serves as the main computational layer.

- **User Dashboard:** The user dashboard provides a view of the current landslide status and serves as an interface for accessing the geo-fenced risk map, safe route planner, and emergency alert notification. This dashboard is accessible to all active users and administrators.

III. METHODOLOGY

Our proposed LandSense framework follows an efficient methodology that helps predict the likelihood of a landslide occurrence. First, the data acquisition process consists of collecting the required data from various external resources like Sentinel-1 SAR/InSAR, rain, DEM, Slope, soil moisture, NDVI, and User’s GPS location. The preprocessing step involves cleaning, imputing, encoding, scaling, and preparing the final dataset. This dataset contains all relevant features needed for the prediction module.

In the prediction model, the Random Forest and XGBoost algorithms have been employed, whereby each algorithm predicts the predicted risk of landslide occurrence independently. In addition, the prediction engine takes the final score from the two algorithms and classifies the predicted risk as either Low, Medium, or High based on the score. Next, the Geo-Fencing Module takes the predicted risk and compares it to the user’s GPS location to trigger an appropriate response.

For instance, if the predicted risk is either Medium or High, then the alert generation module is triggered to send out notifications to the targeted users via SMS, WhatsApp, Telegram, and/or the dashboard. Concurrently, the Safe Route Planning module plans the safest escape route using the Dijkstra’s algorithm. All notification responses are managed by the FastAPI, while the results are displayed using the Streamlit dashboard.

IV. MACHINE LEARNING ALGORITHMS

A. Random Forest:

This algorithm is an ensemble learning method that uses multiple decision trees to make accurate predictions when compared to just using a single decision tree. In other words, it operates by growing several trees and using a random subset of the training dataset for each tree. Finally, every decision tree will make a certain prediction, and the algorithm will pick the most common prediction as the final result.

In our proposed system, the Random Forest algorithm uses various environmental features to predict the likelihood of landslides. It can also handle both categorical and numerical features very effectively to generate reliable results.

Example: We grow 100 decision trees and 82 trees predict High Risk, while 18 trees predict Medium Risk, then the Random Forest algorithm will predict High Risk.

B. XGBoost:

This algorithm is also known as Extreme Gradient Boosting, and it works by creating decision trees that correct themselves. For instance, the first tree makes a certain prediction, and the second tree will make another prediction based on the result of the first one and so on. Finally, it settles with the best accurate prediction to be used as a final result.

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Like the Random Forest algorithm, XGBoost uses environmental features to predict the likelihood of landslides. In addition, this algorithm can handle missing data and manage complex non-linear relationships in the dataset.

Example: Assuming our first model predicts a value of 65%, and subsequent models predict 70%, 72%, 76%, 80%, 85%, and 91% respectively, then the final prediction will be 91%.

C. Ensemble Learning (Random Forest + XGBoost):

The proposed system employs the best of both algorithms (i.e., Random Forest + XGBoost) to predict the likelihood of landslides. In this case, we have combined the two algorithms, so that we get accurate and reliable results for prediction purposes. Finally, the algorithm picks the prediction value with the highest accuracy as the final result.

In most cases, ensemble learning algorithms perform better than standalone algorithms. The algorithm will produce the final predicted value of landslides based on the two previous examples and then the Geo-Fencing Module will take over to activate the relevant response mechanism.

Example: The first algorithm predicts a value of 88%, and the second algorithm predicts 92% value, so the final prediction will settle at 90% using the ensemble learning framework. This means the system will trigger a location-based alert and safe route recommendation mechanism for all registered users in the affected area.

V. EXPECTED RESULTS

Fig. 7.1 Expected Results

Figure 7.1 illustrates the expected results of the proposed LandSense framework. It demonstrates the predicted landslide risk levels, interactive dashboard, risk map, and real-time alert notifications for effective disaster management. The proposed LandSense framework is expected to offer an efficient, intelligent, and reliable solution for landslide early warning by leveraging the power of machine learning, geospatial analysis, and remote sensing. The combination of Sentinel-1 InSAR-derived deformation, rainfall, terrain attributes, and geo- fencing is expected to enhance the accuracy of existing methods by considering multiple parameters that influence landslide occurrences.

The ensemble learning approach, including Random Forest and XGBoost, is anticipated to yield improved performance in classifying Low, Medium, and High locations with reduced false positives and negatives. In addition, the proposed geo-fencing approach is expected to offer location-based warning services by only notifying users in the High-risk areas.

Finally, the proposed Dijkstra's algorithm is expected to facilitate the identification of the shortest and safest route for evacuees. The FastAPI backend and streamlit dashboard are expected to enable real-time visualization and presentation of the prediction results, environmental information, risk status, and warning alerts. Thus, the LandSense framework is expected to enable effective disaster management by offering an intelligent, reliable, and efficient early warning system for landslides.

VI. CONCLUSION

This survey report discussed the latest developments in the field of machine learning-based landslide early warning systems. Specifically, the report highlighted the latest advances in remote sensing, geo-fencing, and prediction models that have been employed in the design of landslide early warning systems. The discussion presented an in-depth understanding of the approaches, including Random Forest, XGBoost, deep learning, Sentinel-1 InSAR, and Geographic Information Systems. The analysis of the approaches highlighted the strengths and weaknesses of using Random Forest, XGBoost, and other deep learning algorithms in combination with remote sensing and geo-fencing data.

Based on the analysis of the state-of-the-art methods, this study proposed an intelligent landslide early warning system that integrates data acquisition, pre-processing, ensemble machine learning, geo-fencing, classification, alert system, safe route recommendation, and dashboard visualization. The proposed approach takes a modular approach to developing the early warning system, thus enabling the use of alternative solutions in case of failure or shortcomings with the proposed solutions. Future directions include the adoption of Explainable AI, Transformer-based models, Graph Neural Networks, real-time processing of Sentinel-1, IoT, and cloud-based disaster management systems.

Finally, the proposed solution showcases the potential of leveraging AI, remote sensing, and geospatial technologies in disaster management. Future directions for this study could include empirical validations of the proposed approaches and the adoption of multiple data sources in the development of early warning systems for landslides.

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