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Machine Learning Based Real Time Landslide Detection and Alert System

Suma Sekhar, Associate Professor, LBS Institute of Technology for Women, Thiruvananthapuram, Kerala, India, sumasekhar@lbsitw.ac.in

Adhithya V. R., LBSITW, Thiruvananthapuram, Kerala, India, adhithyavr77@gmail.com

Ansi S. S., LBSITW, Thiruvananthapuram, Kerala, India, ansishahabdeen@gmail.com

Devika V. R., LBSITW, Thiruvananthapuram, Kerala, India, devika2003vinod@gmail.com

M. Jezmiya Sulthana, LBSITW, Thiruvananthapuram, Kerala, India, jezmiyasulthana@gmail.com

Abstract: By incorporating machine learning (ML) models to the traditional landslide detection (LSD) techniques, the predictive capabilities of the system can be considerably enhanced and the disaster management system can be significantly reinforced. As the ML algorithm can identify the nonlinear relationships between multiple landslide factors more effectively and detect the hidden patterns the traditional models might skip, the accuracy of the LSD system can be remarkably enhanced. In this paper, the implementation of an improved LSD method utilizing random forest algorithm and automated alert mechanism is presented. Using integrated IoT sensors, key environmental factors like soil moisture, vibration, and temperature that influence landslides are continuously monitored and processed allowing real time land slide predictions and early warnings. As soon as a disaster threat is detected, an app-based alert system categorizes risk into three zones: high risk, moderate risk, and safe and sends location-based notifications to local authorities and residents. This enables precautionary measures including quick evacuation or measures and minimizes loss of life and property.

Keywords — Landslide detection (LSD), machine learning (ML), Random Forest, real-time monitoring, IoT sensors, early warning system, risk assessment, app-based alerts.

I. Introduction

Landslides are one of the most destructive natural disasters worldwide, capable of causing significant damage to property, infrastructure, and human lives. To manage landslides effectively, it is crucial to predict potential landslide events early and assess the risk in a timely manner. However, traditional methods for landslide monitoring often lack real-time monitoring and predictive accuracy, which delays response efforts and increases the risk to affected areas. Traditional monitoring methods, like geological surveys and satellite imaging, have been helpful, but they come with major drawbacks. They're often slow, expensive, and not always accurate enough to detect early warning signs. By the time a landslide is identified, it might already be too late to prevent damage or save lives. So a rapid automated and accurate landslide detection system is critical for emergency management and disaster mitigation [1]. The integration of ML algorithms into traditional LSD methods add a lot of privileges to the system including faster processing of geospatial data, automated feature extraction, cloud based implementations for large scale analysis, better insight regarding probability of occurrence of landslides and hence predictions with better accuracy. [2,3,4,21,22].

A more advanced and practical approach by using smart technology to monitor landslide risks in real time is presented in this paper. IoT enabled sensors are deployed to continuously track key environmental factors like soil moisture, temperature, and ground vibrations, giving us live data on conditions that could lead to a landslide. Instead of relying on guesswork, we use the Random Forest algorithm which is a powerful machine learning model to analyze patterns in this data and predict potential landslides with high accuracy. Random Forest is a strong promise in land slide detection system when incorporated with IoT sensors like moisture sensors, accelerometers, vibration sensors, cloud-based data base and real time systems for monitoring and analysis.[5,6] One of the key features of this system is its real-time alert mechanism. The system doesn't just detect risk; it categorizes it into three clear levels high, moderate, and safe, so people know exactly how serious the threat is. These alerts are sent instantly through a mobile app, ensuring that those in danger receive timely and actionable warnings. Whether it's evacuating high-risk areas or taking necessary precautions, these alerts give communities the chance to prepare, reducing panic and

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confusion. Emergency response teams also benefit by being able to allocate resources more efficiently, ensuring help gets where it's needed most. With climate change, deforestation, and rapid urbanization increasing the frequency of landslides worldwide, having a reliable, real-time warning system is more important than ever.

The rest of the paper is organized as follows. In Section 2 the traditional methods for land slide detection are reviewed. Section 3 briefly explains the methodology used for gathering, analyzing and interpreting the data acquired from real time environmental sensors is discussed. Hardware and software requirements for successful implementation of the system are explained in sections 4 and 5. In section 6, performance of the proposed system is evaluated through results. Finally conclusions are drawn in section 7.

II. TRADITIONAL METHODS FOR LAND SLIDE DETECTION

A. *Satellite Imagery*

Satellite imagery aids in mapping vulnerable areas where terrain changes across extensive regions can be monitored using high-resolution satellite images. Landslide risks are identified by analyzing visual data on topographical alterations and surface shifts [7,8].

B. *Surveillance Using Unmanned Aerial Vehicles (UAVs)*

Unmanned aerial vehicles (UAVs) or drones equipped with cameras capture aerial images of landslide-prone locations. Based on close-up real-time perspectives acquired from these images, 3D map models are developed enabling precise visual inspection of the structural shifts that lead to landslides. [9]

C. *Seismographic Sensors*

Seismographic sensors measures ground tremors to detect movement in the earth's crust, signaling potential landslide activity. These sensors placed at high-risk zones record seismic waves generated by soil or rock displacement, capturing even subtle shifts. The signals from sensors are then analyzed with specific tools and software to provide real-time alerts [10].

D. *Field Surveys*

The probability of occurrence of landslide can be identified by recording surface displacements. By monitoring and characterizing the displacement process, the individual part of moving block can be differentiated. It involves on-site inspections by experts who assess soil conditions, slope stability, and visible indicators of potential landslides. These surveys provide hands-on analysis and are essential in areas where soil and geological factors require closer examination to determine vulnerability, creating a detailed risk assessment [11,12].

E. *Weather Forecasting*

Climate change scenarios that cause higher intensity storms, heavy rainfall, and vegetation with weaker root structure or less root biomass will contribute to landslide events. By assessing weather patterns, meteorologists can identify periods of high risk, especially in areas prone to rainfall-induced landslides, enabling proactive planning and alerts before severe weather events [13]

F. *Geological Mapping*

Geotechnical monitoring data represent key inputs for landslide prediction modeling and landslide stability analysis. Maps that detail geological features, historical landslides, and soil composition are created to highlight vulnerable zones. This mapping provides a foundation for understanding landslide-prone areas for developing zoning policies and designing structures with awareness of local geological hazards [14,15]

G. *Ground-Based Radars*

It uses radar technology to measure soil displacement and detect subtle ground movement, offering precise monitoring in landslide-sensitive areas. By identifying shifts within the ground, radars allow for early detection of slope instability, especially effective in monitoring critical structures and populated areas [16,17].

H. *Electrical Resistivity Tomography (ERT)*

ERT uses electrical currents to measure subsurface resistivity, maps soil and rock layers and evaluate the percentages of sand and clay, in soils or rocks within a certain clay content. This method detects changes in moisture content and soil composition, revealing hidden instability that may contribute to landslides, especially in areas with varying underground water levels [18,19].

III. METHODOLOGY

A. *Data Collection*

It involves gathering real-time environmental data using multiple sensors to monitor soil stability and atmospheric conditions. A Vibration Sensor (SW-420) is used to detect ground vibrations and seismic activity that may indicate potential landslides. The Temperature and Humidity Sensor (DHT-22) measures atmospheric temperature and humidity, which influence soil moisture and stability. Additionally, a Rainfall Sensor monitors precipitation levels to assess the impact of heavy rainfall on soil conditions. The Arduino IDE is utilized for programming and calibrating the sensors, allowing efficient data acquisition via microcontrollers.

B. *Data Pre-Processing Stage*

It focuses on refining the raw sensor data to eliminate noise and enhance accuracy before analysis. This involves handling missing or incomplete data to maintain data integrity, filtering outliers to remove inconsistencies, and normalizing data for consistency across different sensor inputs. Python libraries such as Pandas, NumPy, and SciPy

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are used for data cleaning, processing, and statistical analysis, ensuring that the data is reliable for machine learning models.

Machine Learning-Based Prediction a predictive model is developed using advanced machine learning techniques to analyse preprocessed data and assess landslide risks. The Random Forest (RF) algorithm is employed for model training due to its high accuracy in handling environmental data variations. The model continuously adapts and updates with new data to enhance predictive performance. Scikit-Learn is used for model training, evaluation and risk assessment

C. Data Storage and Management

It ensures secure and reliable storage of both real-time and historical sensor data. The cloud-based platform ThingSpeak is utilized to store sensor readings, enabling real-time data retrieval for analysis and visualization. This allows seamless access to historical trends and enhances predictive analytics for landslide monitoring

D. User Interface and Alert System

It is developed to provide real-time risk assessment and warnings to users through a mobile application. The application features color-coded risk alerts, where red signifies high risk requiring immediate action, yellow indicates moderate risk demanding caution, and green represents low risk or safe conditions. Additionally, the app provides live data visualization, allowing users to monitor sensor readings and risk predictions in real time. Push notifications are integrated to issue early warnings and emergency alerts. The app also provides emergency helpline numbers. The application is developed using MIT App Inventor and Dart, ensuring an interactive and user-friendly interface for effective disaster management.

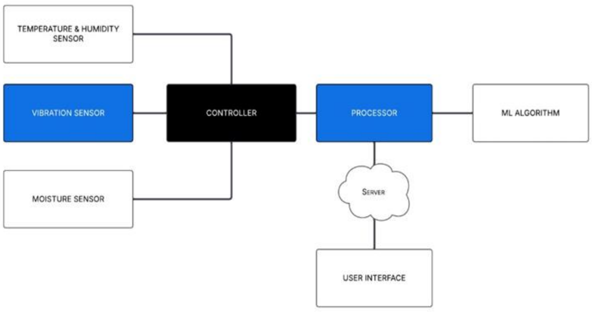

Figure 1: Block schematic of ML based LSD system.

IV. HARDWARE REQUIREMENTS

The functional units required for the implementation of ML based LSD system is as shown in Figure 1.The Arduino Nano serves as the core processing unit, continuously or periodically reading data from multiple environmental sensors to monitor real-time conditions. It efficiently converts analog signals into digital data for further analysis and decision-making, ensuring precise monitoring of environmental changes. The vibration sensor is crucial for detecting ground movements, capturing even the slightest changes in motion. By converting physical vibrations into electrical signals, it allows the system to assess abnormal ground activity that may indicate an impending landslide. These highly sensitive sensors can detect both high- and low-frequency vibrations and are designed to withstand harsh environmental conditions. The temperature and humidity sensor provides dual environmental monitoring by measuring ambient temperature and relative humidity. It ensures accurate readings through digital calibration, offering high precision and long-term stability. Tracking atmospheric changes helps assess factors that contribute to soil destabilization, improving the system's predictive capabilities. The soil moisture sensor determines the water content in the soil using probes to measure conductivity or capacitance changes caused by moisture variations. It provides real-time monitoring with high sensitivity, ensuring accurate soil saturation detection. Since excessive moisture can weaken soil structure, this sensor is vital for predicting landslides. It also operates with low power consumption, making it ideal for deployment in remote areas. The Raspberry Pi plays a crucial role in enhancing the system's computational power and connectivity. Acting as a secondary processing unit, it manages large-scale data processing, enabling complex machine learning models like the Random Forest algorithm to analyze sensor data more efficiently. It also facilitates real-time communication between the sensors and the mobile application, ensuring seamless transmission of alerts to authorities and residents. Additionally, the Raspberry Pi supports cloud integration, allowing data storage, remote access, and further analysis for long-term risk assessment. Together, the Arduino Nano, Raspberry Pi, and various sensors create a robust environmental monitoring system capable of detecting early signs of landslides. By combining real-time data collection with advanced processing and wireless connectivity, the system enables proactive risk management and timely alerts, ultimately minimizing the impact of landslides on vulnerable communities.

V. SOFTWARE REQUIREMENTS

The experiments show that GCP sequence provides better correlation properties in terms of low autocorrelation properties, flat spectrum, low values for ISL and higher values for merit factor. The software requirements for this system ensure seamless data processing, machine learning integration, and real-time monitoring. The Anaconda environment serves as a comprehensive Python distribution, streamlining package management and ensuring efficient installation of essential libraries like NumPy and Scikit-learn. The Jupyter Notebook IDE provides an interactive coding environment, allowing real-time execution and data visualization, making it ideal for testing and analyzing sensor data. The system is built using Python, a versatile and widely used programming language, offering extensive libraries for data analysis, sensor integration, and machine learning applications. The Windows operating system

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ensures broad compatibility and a user-friendly interface while supporting essential development tools and cloud integration with ThingSpeak, a cloud server platform enabling real-time data visualization and remote monitoring for early landslide detection. For mobile application development, MIT App Inventor provides a drag-and-drop interface, simplifying the creation of a user-friendly app to deliver real-time alerts and sensor data. The system relies on key libraries, including NumPy for efficient numerical data processing and Scikit-learn for robust machine learning and predictive modeling, ensuring accurate landslide detection.

VI. RESULTS

A. *Sensor Data Acquisition*

The system successfully collected real-time sensor data from vibration, soil moisture, humidity, and temperature sensors connected via an Arduino microcontroller. These sensors provided continuous environmental measurements, which are critical for monitoring landslide-prone areas. The data was transmitted and stored for further processing, ensuring a reliable foundation for the machine learning pipeline. As shown in Figure 2, the system captures real-time data from each sensor, where the vibration sensor detects ground movement, the soil moisture sensor measures water content in the soil, the humidity sensor tracks atmospheric moisture levels, and the temperature sensor records temperature variations. The figure also illustrates how these sensors are interconnected with the Arduino microcontroller, enabling seamless data transmission for further analysis. The integration of multiple sensors enhances the accuracy of landslide prediction by capturing diverse environmental parameters. Additionally, the system's ability to collect real-time data ensures that even minor changes in environmental conditions can be detected, allowing for early warnings and preventive measures.

```
Humidity: 74.30%  Temperature: 31.00°C 87.80°F  Heat index: 38.94°C 102.10°F
Moisture State: 1    Vibration State: 0

Humidity: 74.30%  Temperature: 31.10°C 87.98°F  Heat index: 39.24°C 102.63°F
Moisture State: 1    Vibration State: 0

Humidity: 74.00%  Temperature: 31.00°C 87.80°F  Heat index: 38.85°C 101.92°F
Moisture State: 1    Vibration State: 1

Humidity: 74.30%  Temperature: 31.10°C 87.98°F  Heat index: 39.24°C 102.63°F
Moisture State: 1    Vibration State: 0

Humidity: 74.30%  Temperature: 31.00°C 87.80°F  Heat index: 38.94°C 102.10°F
Moisture State: 1    Vibration State: 0

Humidity: 74.40%  Temperature: 30.90°C 87.62°F  Heat index: 38.68°C 101.63°F
Moisture State: 1    Vibration State: 0
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Figure 2: Data collected from each sensor

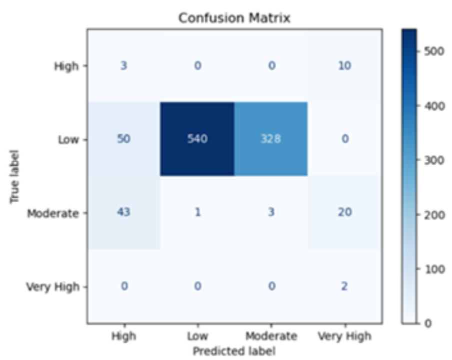
B. *Machine Learning Model Evaluation and Selection*

Several Machine Learning algorithms, including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Random Forest (RF), were tested and evaluated for their performance in landslide detection. Both balanced and unbalanced datasets were used to train and validate the models. The evaluation metrics included ROC-AUC score, F1 score, and confusion matrix analysis.

The performance of RF with unbalanced data is illustrated in Figure 3, which includes (a) a classification report showing the precision, recall, and F1 score, (b) an AUC-ROC curve confirming strong predictive capability, and (c) a confusion matrix highlighting the classification accuracy and misclassification rates. Similarly, Figure 4 presents the performance of KNN, detailing (a) the classification report to analyze accuracy and error rates, (b) an AUC-ROC curve demonstrating model sensitivity, and (c) a confusion matrix reflecting the distribution of correct and incorrect classifications. For SVM performance, Figure 5 provides insights into (a) the classification report showing precision, recall, and F1 score, (b) an AUC-ROC curve assessing landslide prediction accuracy, and (c) a confusion matrix representing classification results. Finally, Figure 6 depicts RF performance with balanced data, where (a) the classification report highlights the impact of resampling on model accuracy, (b) the AUC-ROC curve illustrates improved classification performance, and (c) the confusion matrix shows better class distribution and fewer misclassifications. The Random Forest model was selected as the best-performing algorithm due to its high ROC-AUC score and its ability to handle imbalanced datasets effectively. The use of Scikit-Learn for model training, evaluation, and optimization ensures robust and reproducible results, making this approach highly reliable for landslide prediction.

Classification Report:

	precision	recall	f1-score	support
High	0.03	0.23	0.06	13
Low	1.00	0.59	0.74	918
Moderate	0.01	0.04	0.02	67
Very High	0.06	1.00	0.12	2
accuracy			0.55	1000
macro avg	0.28	0.47	0.23	1000
weighted avg	0.92	0.55	0.68	1000



ROC-AUC Score: 0.5008

Figure 3: RF (Unbalanced) Performance (a) Classification report, (b) AUC-ROC curve, and (c) confusion matrix for RF with unbalanced data.

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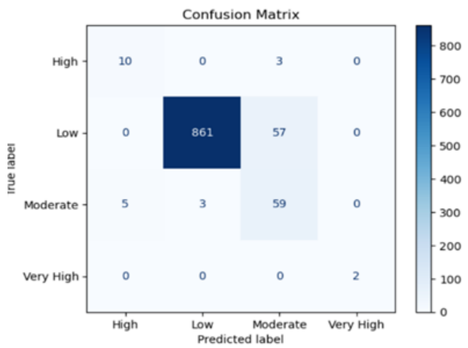
Classification Report:

	precision	recall	f1-score	support
High	0.67	0.77	0.71	13
Low	1.00	0.94	0.97	918
Moderate	0.50	0.88	0.63	67
Very High	1.00	1.00	1.00	2
accuracy			0.93	1000
macro avg	0.79	0.90	0.83	1000
weighted avg	0.96	0.93	0.94	1000

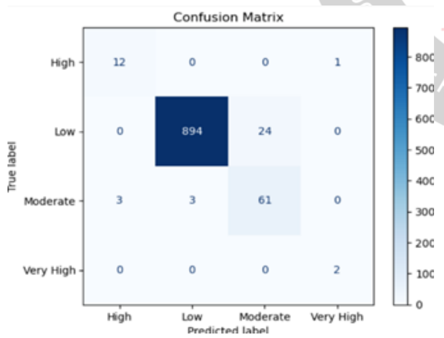


ROC-AUC Score: 0.9698

Figure 4: KNN Performance (a) Classification report, (b) AUC-ROC curve, and (c) confusion matrix for KNN

Classification Report:

	precision	recall	f1-score	support
High	0.80	0.92	0.86	13
Low	1.00	0.97	0.99	918
Moderate	0.72	0.91	0.80	67
Very High	0.67	1.00	0.80	2
accuracy			0.97	1000
macro avg	0.80	0.95	0.86	1000
weighted avg	0.97	0.97	0.97	1000

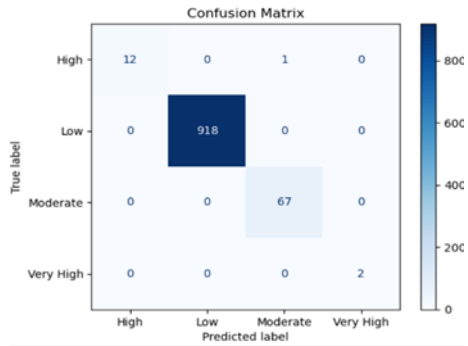


ROC-AUC Score: 0.9976

Figure 5: SVM Performance (a) Classification report, (b) AUC-ROC curve, and (c) confusion matrix for SVM

Classification Report:

	precision	recall	f1-score	support
High	1.00	0.92	0.96	13
Low	1.00	1.00	1.00	918
Moderate	0.99	1.00	0.99	67
Very High	1.00	1.00	1.00	2
accuracy			1.00	1000
macro avg	1.00	0.98	0.99	1000
weighted avg	1.00	1.00	1.00	1000



ROC-AUC Score: 1.0000

Figure 6: RF (balanced) Performance (a) Classification report, (b) AUC-ROC curve, and (c) confusion matrix for RF with balanced data.

C. Mobile Application Development

A mobile application named "GeoAlert" was developed using Flutter to provide an intuitive interface for real-time monitoring and risk prediction. The app features live data visualization, allowing users to track sensor readings and landslide risk levels dynamically. Additionally, "GeoAlert" incorporates push notifications to deliver early warnings and emergency alerts, ensuring a timely response to potential landslide events. The user interface of the app is illustrated in Figure 7, which includes screenshots of the main dashboard displaying real-time sensor readings, a visual representation of landslide risk levels, and sample push notification alerts for emergency warnings. The app also includes a dedicated section for emergency precautions and contacts, offering users critical information and resources during emergencies. By integrating real-time alerts, a user-friendly interface, and live sensor data visualization, the GeoAlert application enhances disaster preparedness and helps in proactive decision-making, making it a valuable tool for landslide-prone areas.

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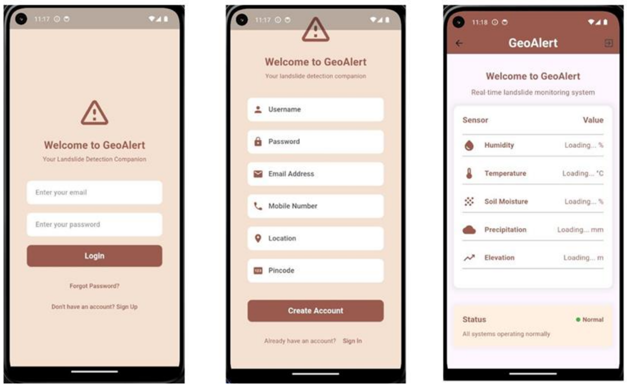

Figure 7: User Interface of GeoAlert App

VII. CONCLUSION AND FUTURE SCOPE

A reliable land slide prediction system is successfully implemented by integrating sensor-based data acquisition, machine learning algorithms, and a mobile application for real-time alerts. A user friendly mobile application "Geo Alert" is developed and integrated to this LSD system for providing automated alert mechanism and accelerating the decision making. One of the standout features of the app is its ability to visualize risk levels, allowing users to monitor environmental conditions such as rainfall, soil moisture, and ground stability through an intuitive dashboard. When a landslide risk escalates, push notifications are implemented to issue immediate warnings in surrounding areas. This helps users and authorities to take necessary precautions including evacuation measures in time. Additionally, the app includes emergency preparedness resources, offering step-by-step safety guidelines, emergency contacts, and helpline numbers for disaster response. This enhances public awareness and preparedness, helping communities respond effectively to potential landslide threats. Hence this early LS detection system offers a cost effective solution for significantly reducing the impacts of the disaster by saving valuable human lives, minimizing losses, and building resilience against future disasters.

The future scope for upgrading the system includes integrating artificial intelligence powered interactive features to the mobile app and enhancing the adaptability of the predictive model to more distinctive terrains. The accuracy of the system can be enhanced to a greater extend by elaborating the data set in the model with more diverse geographical data like atmospheric pressure, soil composition and underground water levels. The effectiveness of the app can be further enhanced through AI powered chat support and natural language processing where, the urgent queries regarding emergency services and rescue operation can be quickly responded through the automated responses in the language selected by the customer.

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