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EARLY PREDICTION OF LANDSLIDE USING IOT AND DEEP LEARNING MODEL

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Abstract:

Landslides are the most dangerous natural hazards, often occurring without warning and causing significant loss of life, property damage, and environmental destruction. Accurate and timely prediction of landslides is essential for effective disaster management and risk mitigation. This project presents a machine learning–based landslide prediction system using a Random Forest classifier to analyse multiple environmental and geological parameters influencing landslide occurrence.The proposed system utilizes features such as rainfall intensity, slope angle, soil saturation, vegetation cover, earthquake activity, proximity to water bodies, and soil type to predict the likelihood of a landslide. Standard normalization methods are used to preprocess and scale the input data in order to boost model performance. The trained machine learning model determines whether the situation is safe or high-risk and provides an estimate of the likelihood of a landslide occurring. To enable real-time integration with embedded and IoT systems, the prediction results are transmitted through serial communication at 9600 baud rates in a simple comma-separated

***Index Terms*—Random Forest algorithm, IOT, Embedded systems**

I. INTRODUCTION

Landslides rank among nature’s most destructive events.This chapter opens by looking at how they unfold across regions. Sudden ground shifts define their impact. Not every slope gives warning before collapse. Movement often follows heavy rain or quakes. Terrain stability plays a key role.Some areas face risk more than others.Understanding triggers helps reduce harm. Early signs matter for communities nearby. Each event shapes landscapes differently. Hills shape the land where storms roll in often. Rain falls heavily when clouds hit steep slopes. Weather turns wet as air rises over peaks. Moisture clings to valleys after downpours pass.

Floods often start when heavy rains soak the ground, yet people sometimes build homes in risky spots. Soil can’t absorb water fast enough after downpours, especially where trees have been cleared. When rivers swell past their banks, nearby areas get swamped without warning.Urban drainage systems may fail under intense storms,making things worse slowly at first then suddenly bumpy ground shifts under uneven layers of earth.
Quakes rattle hidden cracks below. Trees vanish where soil breaks apart easily. Movement hides beneath what looks solid at first glance.Floods, earthquakes, and storms often leave behind deadly outcomes.Lives are lost when shelters collapse or rescue fails to arrive on time. Broken bridges cut off entire towns from help. Rail lines twist under pressure, halting supply movements. Power grids flicker out after quakes shake transmission towers; loose machines might fail, causing harm to nature around them. Ahead of events like landslides, spotting risks early makes a real difference.How warnings unfold can shape what comes next. Back then, people watched the land closely by hand. Earlier warnings came from old records of slides that already happened. Instruments placed on top gave clues about movement.These methods worked together to spot danger signs A specific point must be reached before anything changes.Even if this info helps, it misses how things twist together in messy ways A chain of conditions shapes how landslides unfold. One piece leads to another, often without warning. Pressure builds where water meets soil. Movement follows shifts deep below.Each element plays its part, unseen until it isn’t. Because of this, older landslide alert methods might not reach folks quickly enough - or clearly enough - to keep them safe. Mistakes can set off slides when timing is critical. The development and implementation of intelligent landslide prediction systems, with the ability to process large patterns hiding in environmental information can now be found because of new advances in technology. These breakthroughs make it easier to explore complex datasets without slow methods. Machines learn from examples, then spot trends humans might miss. Insights once buried under noise are now visible through smarter tools.

II. Related Work

Early Landslide Prediction Using IoT and Machine Learning Techniques presents an IoT-based landslide prediction system integrated with machine learning techniques to improve early warning accuracy in landslide-prone regions. Environmental and geological parameters such as rainfall intensity, soil moisture, slope angle, vibration, and ground movement are collected using sensors. The data is analyzed using machine learning algorithms to predict landslide probability. The system aims to reduce disaster impact through early alerts. However, the implementation focuses more on data analysis and lacks simplified integration with embedded alert systems.The main limitations are Limited real-time field validation,Complex deployment architecture and High dependency on sensor availability.

Landslide Detection and Monitoring System Using Internet of Things proposes an IoT-based landslide detection and monitoring system that continuously observes environmental parameters such as soil moisture, rainfall, and ground vibration.Threshold-based logic is used to detect abnormal conditions and generate alerts. The system improves monitoring efficiency compared to manual observation. However, it does not incorporate intelligent prediction models and relies only on predefined threshold values.The main disadvantages here are ,no machine learning-based prediction,High false alarm probability prediction and Limited accuracy in complex terrain.Machine Learning Approach for Landslide Hazard Prediction investigates the use of machine learning techniques for predicting landslide hazards based on historical datasets. Parameters such as rainfall,slope angle, soil type, and vegetation cover are analyzed to classify landslide-prone regions. The study demonstrates improved accuracy over traditional statistical methods but lacks real-time alert mechanisms and hardware integration.

Real-Time Landslide Monitoring Using IoT Sensor Networks:This paper presents a real-time landslide monitoring system using IoT sensor networks deployed in landslide-prone regions. Sensors continuously monitor slope stability and environmental changes. The system enables early detection of abnormal conditions but does not perform predictive analysis, limiting its ability to provide advance warnings.

Landslide Prediction Using Random Forest Algorithm explores the use of the Random Forest algorithm for predicting landslide occurrences using environmental parameters. The model shows high accuracy and robustness compared to single classifiers. However, the study remains simulation-based and does not include real- time alerting or embedded system integration. IoT-Based Early Warning System for Landslides:This paper proposes an IoT-based early warning system for landslides using environmental sensing and wireless communication. The system improves monitoring coverage but relies on static thresholds and lacks adaptive prediction capabilities.

III. Proposed System

The proposed system introduces an intelligent, machine learning–based approach for landslide and early warning. It integrates environmental data analysis, random forest prediction,and serial communication to build a reliable and real-time landslide risk assessment system. The machine learning model processes multiple environmental and geological parameters to calculate the probability of landslide occurrence. based on a predefined threshold, the system classifies the condition as safe or landslide risk. The prediction output is transmitted to an embedded system such as arduino or ESP32 via serial communication, enabling real-time alert generation using leds, buzzers, or IOT--based notification systems.Fig.1 shows architectural diagram of the system.

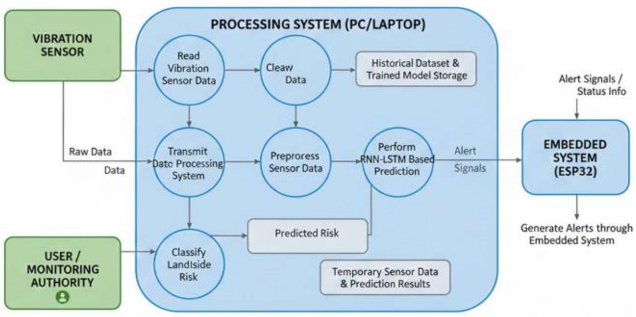

Fig1. Architectural Diagram

1) Dataset Characteristics:

A sudden spike in rainfall often shows up before trouble begins. One reading at a time, the system gathers how wet the ground is. Moisture builds slowly, sometimes hidden under steady slopes.Conditions shift when angles tilt past normal ranges. These signals appear again and again just before movement happens. Learning starts by comparing calm moments with tense ones. Heavy rain plus damp earth gives clear warnings. Past data holds clues about what comes next. Patterns form where water collects and land slips. Every entry marks a moment caught before disaster strikes.

	A	B	C	D	E	F	G	H	I	J	K
1	Rainfall_m	Slope_Ang	Soil_Satur	Vegetatior	Earthquak	Proximity_	Landslide	Soil_Type_	Soil_Type_	Soil_Type_Silt	
2	206.181	58.275	0.892798	0.339463	4.390047	0.099975	1	0	0	0	
3	218.8873	36.6798	0.657147	0.360355	4.141029	0.832443	1	0	0	1	
4	181.8509	31.36387	0.673362	0.221697	5.311891	0.023062	1	0	0	1	
5	228.7162	38.99513	0.618666	0.489502	4.581928	0.785176	1	0	0	1	
6	179.9511	42.99821	0.836966	0.11858	5.518862	0.450499	1	0	0	0	
7	151.9897	57.97706	0.825315	0.254167	4.039916	0.684233	1	0	0	1	
8	216.0229	29.27134	0.798071	0.113755	6.273301	0.182236	1	0	0	1	
9	263.3042	39.88046	0.683177	0.32708	4.078283	0.775133	1	0	0	1	
10	290.9248	56.31896	0.83916	0.46875	4.221231	0.520834	1	0	0	0	
11	294.1758	54.55868	0.898928	0.315877	5.466878	0.280935	1	0	0	0	
12	231.4044	29.93235	0.920879	0.12982	6.467217	0.394882	1	0	0	1	
13	194.0232	25.49279	0.679537	0.384537	5.975439	0.074045	1	0	0	0	
14	203.7699	29.05542	0.945241	0.349319	4.827245	0.370818	1	0	0	1	
15	250.3262	48.30728	0.836519	0.209889	5.403109	0.119594	1	0	0	0	
16	256.9867	51.62748	0.824511	0.408387	5.234489	0.710663	1	0	0	0	
17	166.6336	40.37678	0.680688	0.458305	5.188426	0.508571	1	0	0	0	
18	286.135	33.72523	0.764153	0.40222	4.571995	0.598865	1	0	0	1	
19	254.2177	55.81637	0.849742	0.218253	4.263736	0.803672	1	0	0	1	

Fig.2 Data set Characteristics

2) Data preprocessing and Scaling:

The collected input data may contain variations in range and scale. Therefore, preprocessing is performed to clean the data and normalize it using standard scaling techniques.This step ensures that all features contribute equally to the prediction process and improves the accuracy of the machine learning model.

3) Random Forest Machine Learning Model:

In this block, the preprocessed data is fed into a trained Random Forest classifier.Random Forest is an ensemble learning technique that uses multiple decision trees to analyze complex relationships among input parameters and predict landslide behavior with high accuracy and reliability.

4) Probability Calculation:

The machine learning model calculates the probability of landslide occurrence based on the learned patterns from historical data. This probability value indicates the likelihood of a landslide under the given environmental conditions.

5) **Risk Classification:**

The calculated probability is compared with a predefined threshold value. If the probability exceeds the threshold, the system classifies the condition as Landslide Risk (1); otherwise, it is classified as Safe (0). This classification simplifies decision-making for alert generation.

6) Serial Communication:

The prediction result is transmitted through serial communication at a baud rate of 9600. The data is sent in a simple comma-separated format, making it easy for embedded systems to receive and interpret the result.

7) **Embedded System (Arduino / ESP32)**:

An embedded controller such as Arduino or ESP32 receives the serial data. This system acts as an interface between the prediction model and the alert mechanisms.

8) Alert and Monitoring System:

Based on the received classification, alerts such as LED indicators, buzzers, SMS notifications, or IoT-based warnings can be triggered. This block enables real-time monitoring and early warning to reduce the impact of landslides.

IV. RESULT ANALYSIS

1. Model Training Results:

Various environmental and geological parameters from a historical landslide dataset were used to train the Random Forest classifier. The Random Forest algorithm constructed multiple decision trees and combined their outputs to improve prediction accuracy and robustness. The model was resistant to overfitting and produced consistent prediction results across multiple test inputs because of its ensemble nature.

2. Prediction Output :

The system generates a specific set of environmental input parametersThe Chance of a Landslide (in Percentage) Risk Classification (0 – Safe, 1 – Landslide Risk) 87.44, 1 .This indicates a landslide probability of 87.44%, which is classified as a high-risk condition. The output format is simple and compact, enabling easy interpretation by embedded systems.

3. Serial Communication Results:

At a baud rate of 9600, the prediction results were sent over serial communication. The communication was found to be:Reliable,Dependable and Free from data loss the embedded system responded appropriately after successfully receiving the data in real time. Compatibility with low– resource microcontrollers like the Arduino and ESP32 was ensured by using a comma- separated format.Resource microcontrollers like the Arduino and ESP32 was ensured by using a comma- separated format.

4. Embedded System Response:

When the prediction output is received: The system indicates a safe condition if the label is 0. The system starts alert mechanisms like LED indicators or buzzers if the label is 1. This immediate response demonstrates the effectiveness of integrating machine learning prediction with embedded hardware for real-time disaster alert systems.

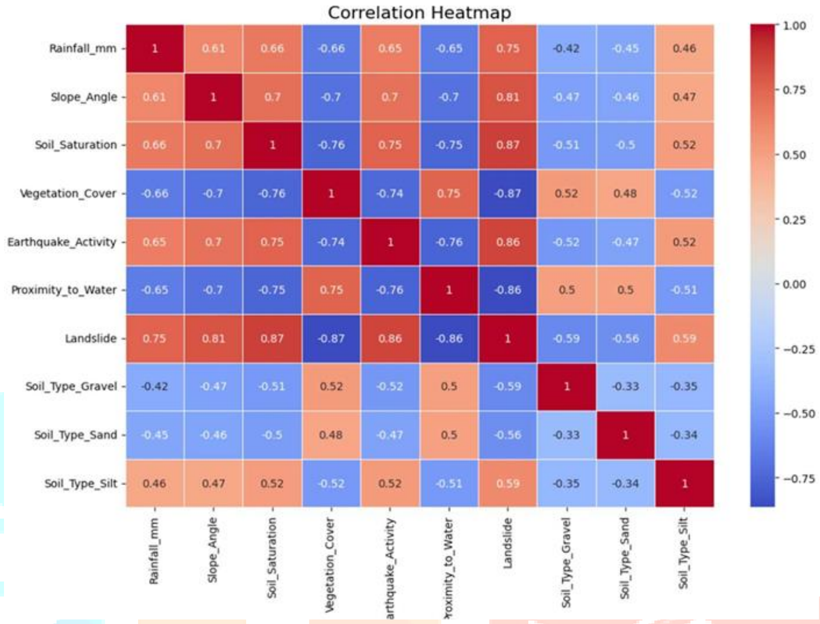

Fig.3.Corelation Heatmap

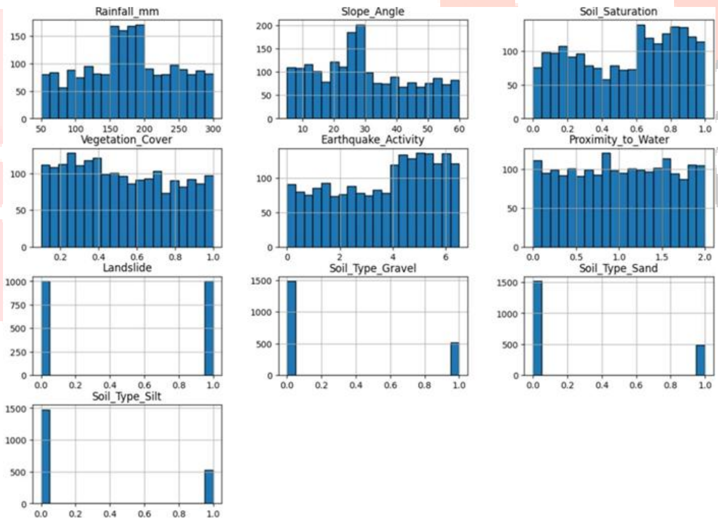

Fig.4 Feature Distribution

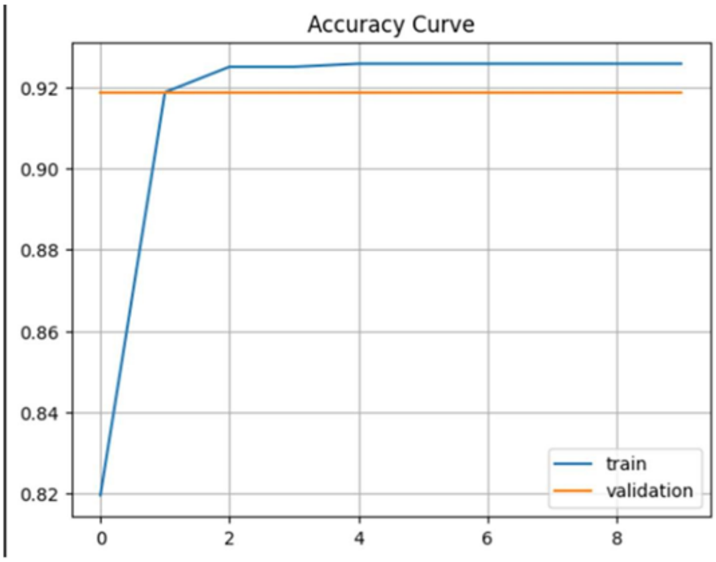

Fig.5 Accuracy Curve

Precision 0.90 → When the model predicts landslide or no landslide, it is right 90% of the time.
Recall 0.90 → The model successfully detects 90% of actual cases.
F1-score 0.90 → Balance of precision and recall is strong. Accuracy 90% → Model detects landslide risk reliably.

V. Conclusion And Future Scope

By utilizing a Random Forest classifier, the system effectively analyzes multiple environmental and geological parameters such as rainfall intensity, slope angle, soil saturation, vegetation cover, earthquake activity, proximity to water bodies, and soil type to predict the likelihood of landslide occurrence. Prediction accuracy and model reliability are significantly improved through the use of feature scaling and data preprocessing. The experimental results show that the system can generate accurate probability-based predictions and classify risk levels efficiently. The system can be enhanced by integrating real-time sensors,cloud platform, adding a GPS based location tracking and can use multilevel risk classification for more accurate landslide prediction. Also integrate GSM modules or cloud- based notification services to send SMS, email, or mobile app alerts to authorities and nearby residents during high-risk situations.

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