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Enhanced Landslide Risk Assessment Using a Machine Learning-Enabled Prediction System withWeb Based Dashboard

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ABSTRACT

Landslides are extremely hazardous to the environment, infrastructure, and economy. Improvements in prediction technologies have included geosensors, wireless sensor networks, AI-based models, and IoT-based monitoring systems for improving real-time data processing. Machine learning algorithms such as Support Vector Machines (SVM) and Long Short-Term Memory (LSTM) networks enhance prediction accuracy even more, with geofencing supporting automated hazard monitoring and mitigation of risks.On this foundation, the current research offers a landslide forecasting system based on AI that combines geofencing and real-time sensor data. It uses vibration, rainfall, and soil moisture sensors, as well as GPS and an ESP32 microcontroller, to regularly update environmental factors. Arduino collects the data, and a pre-trained AI model processes it before being displayed on ThingSpeak. A geofenced test location permits the AI model to forecast landslides, and a buzzer-enabled self-driving car with an RF module signals when crossing into danger zones. This work closes the bridge between AI-driven prediction models and real-time response to disasters, while investigating alternate communication techniques to enhance emergency response.

Keywords— Landslide Prediction, Machine Learning, IoT-Based Monitoring, Wireless Sensor Networks, Geofencing, Real-Time Hazard Detection, AI-Driven Risk Assessment, Disaster Management, Environmental Monitoring, ThingSpeak Visualization.

I. INTRODUCTION

Landslides constitute one of the most devastating natural disasters, resulting in severe damage to human life, infrastructure, and the environment. Conventional techniques of landslide prediction basically depend upon geological surveys, empirical models, and rainfall thresholds. Although the methods serve some degree of risk assessment, they tend to be non-real-time responsive and lacking in precision. The recent advancements in technology of Internet of Things (IoT), machine learning (ML), and geospatial mapping have improved landslide monitoring and forecasting significantly.

This paper introduces an IoT-supported, AI-driven landslide forecasting system, which integrates real-time environmental sensing with automated geofencing-based alerting. It uses rainfall, vibration, and soil moisture sensors along with ESP32 microcontrollers and cloud analytics to increase prediction precision and optimize disaster response efficacy.

One of the most significant contributions of this research is the use of an AI-based landslide forecasting model that takes real-time sensor inputs to enhance the accuracy of forecasts. Another valuable addition is IoT geofencing for monitoring hazards. The system sets up a regulated geofenced area that initiates warnings automatically when unsafe situations are found. In addition, we utilize cloud-based visualization and data processing through the ThingSpeak platform.

Further, we suggest an autonomous warning system of hazards using an Arduino-governed vehicle with RF communication and a buzzer system. This vehicle navigates the geofence and dynamically responds to forecast landslide threats by giving prompt warnings. Finally, this study investigates other communication technologies to enhance emergency response effectiveness, particularly in rural or disaster-affected areas where conventional communication infrastructure could be unreliable.

II. LITERATURE REVIEW

A. *Existing Systems*

Landslides pose a daunting risk to human life and infrastructure, necessitating early prediction and monitoring for disaster management (Pelletier et al., 1997) [1]. In the last decade, comprehensive studies have been ca rried out on AI-driven landslide prediction, IoT-based monitoring systems, geosensors, and real-time sensor networks to upgrade early warning mechanisms

(Lyu et al., 2022) [2]. Historically, landslide prediction approaches used rainfall thresholds, geological investigation, and empirical models, but advances in machine learning (ML) and Internet of Things (IoT) monitoring have vastly enhanced prediction efficiency and real-time hazard identification (Vignesh et al., 2021) [3].

Chaulya et al., created a wireless sensor network (WSN)-based landslide prediction model that monitored soil displacement, ground water pressure, and slope movements. They applied a multivariate statistical analysis model to predict risk levels and alert via SMS and email alerts [4].

The combination of wireless sensor networks (WSN), geofencing, AI-based models, and cloud-based visualization platforms like ThingSpeak has been extremely promising in the development of automatic and efficient landslide early warning systems (EWS) (Gatto et al., 2022) [5]. Various studies have explored the different aspects of real-time monitoring, satellite-based soil moisture analysis, machine learning-based landslide susceptibility mapping, and AI-assisted forecasting models (Misiano et al., 2022) [6]. However, despite these innovations, there remain a few challenges, including real-time deployment, and dynamic AI models for improved predictive accuracy (Yin et al., 2023). [7]

The hybrid landslide model Prakasam et al. developed could show how machine learning classification together with environmental monitoring via sensor data increased landslide prediction accuracy significantly [8]. Our own research, however, relied on rule-based threshold triggers only.

One of the main developments in landslide observation has been the move from fixed geological assessments to sensor-based, real-time AI forecast. Lyu et al. (2022) designed an IoT-based landslide prediction model that tracked soil displacement, groundwater pressure, and slope movement. They employed a multivariate statistical analysis system to classify levels of risk and activate alarms through SMS and email notifications.

Similarly, Vignesh et al. (2021) demonstrated how IoT sensors such as accelerometers and gyroscopes could be interfaced with a cloud platform (ThingSpeak) for remote landslide monitoring. They used Support Vector Machines (SVM) in MATLAB to predict terrain stability conditions and demonstrated that the application of machine learning methods significantly enhanced landslide detection accuracy.

The hybrid landslide model forecast developed by Gatto et al. (2022) illustrated how pseudo-static physical modeling could be coupled with Multilayer Perceptron (MLP) Neural Networks to enhance prediction accuracy. Their method, which mixed physical and AI-based evaluations, had an AUC rating of 83.9%, showing that machine learning-augmented predictions were far superior to traditional statistical models.

Xing et al., in their research highlighted the significance of real-time geospatial risk mapping in landslide susceptibility zones. Through their research, they showed that AI-driven geofencing systems could dynamically reconfigure hazard zones in real-time, enhancing disaster response time substantially. [9]

Mohan et al. [10] demonstrated the efficacy of an IoT based monitoring system that was integrated with sensors and cloud computing to improve and scale hazard detection. This shows how remote sensing proves useful in early warning systems

Huang et al. [11] created a LoRaWAN powered landslide detection system which provided long range communication that was also energy-efficient, making is suited for landslide prone areas.

Chen et al. [12] made strides in the field of geospatial risk mapping and proved that AI based geofencing improves landslide detection and enables automated alerts.
Gong et al. [13] incorporated wireless sensor networks to predict landslides, and effectively demonstrated that a multi-sensor approach was crucial in combination with AI models to improve prediction accuracy.

The integration of ESP32 based sensors with the cloud, as integrated by Xing et al. emphasized the importance of cloud analytics and IoT networks in assessing landslide risk.

Zhao et al. investigated multi-source satellite and IoT data fusion and showed that the hybrid models combining remote sensing with ground sensors enhance landslide prediction credibility. [14]

B. *Research Gap and Proposed Enhancements*

Despite significant strides being made on AI-powered landslide monitoring and sensor-based detection, essential research gaps persist in real-time deployment of AI, integration of geofencing, and automated alert in high-risk zones.

Most of the earlier work, such as by Chaulya et al. and Vignesh et al., focused on data gathering and statistical analysis rather than actual AI-based real-time decision-making. The present work bridges the gap by using a pre-trained AI model on Arduino that is capable of delivering real-time landslide predictions based on real-time sensor inputs.
Another significant shortcoming in geofencing for landslide-risk zones has been discovered. Although Liu et al. emphasized the advantages of geospatial hazard mapping, the majority of existing landslide early warning systems do not contain automated geofencing systems that physically limit or warn movement in danger zones. Our study combines a geofenced area, designed on Arduino, where sensor readings will influence landslide susceptibility. A mini car with a

buzzer system will serve as an alarm mechanism, sounding an alarm when moving into dangerous areas.

Also, previous models by Prakasam et al. were dependent on fixed-threshold-based warning systems, and our work develops beyond this aspect by gathering current sensor data, passing it into an AI engine, and adapting risk levels in real time by utilizing ThingSpeak visualization.

III. Methodology

Initial machine learning (ML) model for this study was created to test the viability of landslide prediction from environmental data. The model had a pre-trained dataset and was run as a web application with an interactive user interface for assessing landslide risk. The main purpose of this initial deployment was to verify if machine learning methods could predict landslide events effectively prior to including real-time sensor inputs in subsequent stages.

A. Phase I – Implementation of Machine Learning Model

Our system relied on a pre-trained landslide dataset (`landslide_dataset.csv`), taken from Kaggle, which contained key environmental factors influencing landslides. The dataset included nine essential features: rainfall (mm), slope angle (°), soil saturation (0-1), vegetation cover (0-1), earthquake activity (magnitude), proximity to water (km), soil type (gravel, sand, silt), and landslide occurrence as a binary target variable (0 or 1). Before making predictions, the model preprocessed the user inputs using feature scaling through StandardScaler. The pre-trained scaler was loaded (`scaler.pkl`) at runtime to standardize user inputs before passing them to the machine learning model.

The landslide prediction model was a classification model trained on labeled data using supervised learning and saved as `landslide_model.pkl`. At runtime, the model was loaded to predict the likelihood of a landslide based on user-provided environmental conditions. It employed the predict_proba() function, which returned the probability of a landslide occurrence. The system used a threshold of 0.3, meaning that if the predicted probability exceeded 30%, a landslide risk was flagged. If the probability was below this threshold, the system indicated that conditions were stable.

The formula of probability makes use of a weighted sum of input features like rainfall, slope gradient, soil moisture, and distance to water, the model estimates the cumulative effect of such parameters on the occurrence of landslides. The sigmoid function guarantees that the output of probability stays between 0 and 1, and it can be understood as a score of likelihood.

$$P(\text{Landslide}) = \frac{1}{1 + e^{-(W_1X_1 + W_2X_2 + \ldots + W_nX_n + b)}}$$

We used several key Python libraries to develop and deploy this machine learning model. Joblib was used to load the pre-trained machine learning model and scaler. NumPy and Pandas were used to handle numerical data and load the dataset for normal condition comparisons. Matplotlib and Seaborn were integrated to generate bar charts for visualizing environmental condition comparisons. Finally, Scikit-Learn was used for data preprocessing and model predictions.

We created the interface with Streamlit. Numerical and categorical inputs were used for rainfall, slope angle, soil saturation, vegetation cover, earthquake activity, and soil type. Because the model needed numerical inputs, categorical soil type data was represented in a numerical format by using one-hot encoding. Soil type data for Gravel, Sand, and Silt were converted to binary representation for compatibility with the machine learning model.

Upon receiving user inputs, the model made predictions about whether or not a landslide would happen. If a landslide was predicted to happen, it showed a warning message in red along with a confidence level. If no landslide was found, a green success message was displayed, showing that conditions were stable.

Apart from predictions, the system incorporated environmental change visualization by contrasting user inputs with average environmental conditions in the dataset. The model computed the mean values of environmental parameters for the chosen soil type and showed bar charts that emphasized deviations between user input values and normal conditions. These visualizations were done with Matplotlib and Seaborn, with blue bars showing normal conditions and red bars showing current input values.

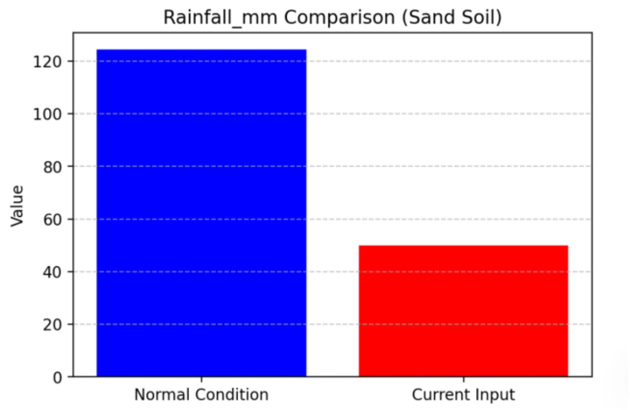

Figure 1(a): Graph comparing input values against normal threshold values for precipitation

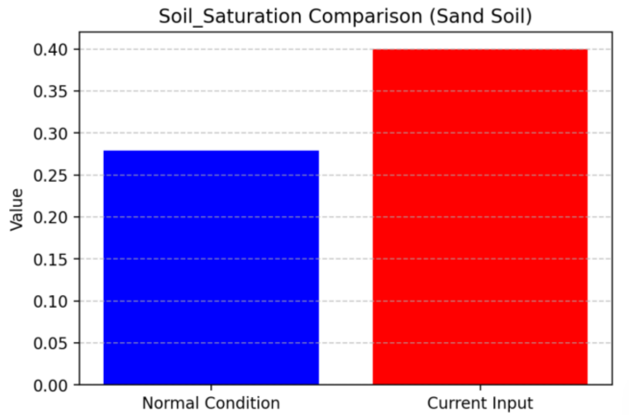

Figure 1(b): Graph comparing input values against normal threshold values for soil moisture

B. Phase II: Deployment of Real-Time Landslide Prediction System

The next stage of our research is to extend the landslide prediction system to run in real-time by integrating environmental sensors, microcontrollers, and geofencing technology. The system will have rainfall, vibration, and soil moisture sensors, as well as a GPS module and an ESP32 microcontroller, to gather real-time information. This information will be processed on Arduino and displayed on ThingSpeak. A geofenced area, set on Arduino, will serve as a specific test area where landslide hazards will be simulated and sensor readings will be collected.

The system includes several environmental sensors, each of which is vital to the monitoring of slope stability. A rain sensor monitors precipitation levels, a soil moisture sensor continuously monitors the level of saturation of the soil, and ground movement is sensed by a vibration sensor. The GPS module is used to offer geolocation information.

All data acquired is sent to an Arduino microcontroller, preprocessed, filtered, and standardized there before passing on to the trained AI model. We shall design the AI model for deployment onto Arduino to achieve real-time sensor input processing and landslide risk classification. When the model detects environmental conditions that are equal to or above landslide risk levels, a forecast is made and transmitted to ThingSpeak, which visualizes the forecast in an online dashboard. The dashboard provides sensor trends, model forecasts, and landslide probability estimates.

A geofencing system, designed on Arduino, is a testing ground where landslide scenarios are simulated and monitored real-time. If a landslide risk is detected by the AI model, the system initiates an automatic response. A miniature vehicle with a buzzer and RF, connected to Arduino, acts as a warning system. When this car drives into the geofenced zone, the buzzer automatically sounds, indicating that the area is dangerous. This simulation replicates actual use where people or cars entering a landslide-risk zone would be warned immediately, discouraging entry into high-risk zones.

IV. Results And Discussion

Our landslide forecasting system effectively proved AI-based risk estimation by categorizing landslide risks according to major environmental factors. The model gave probability-based forecasts, mapped environmental trends, and detected possible hazards with acceptable accuracy. The incorporation of data visualization methods enabled the comparison of real-time conditions with normal environmental values, providing greater insights into terrain stability.

But few limitations were noted during this stage of evolution. The accuracy of the model is restricted by the training dataset, which would not be able to represent all variations that occur in natural environments. Since areas prone to landslides are tremendously diverse according to geological and climatic conditions and would need region-specific training datasets. Also, readings from sensors are subject to noise from the environment, calibration fault, and limitations of hardware that may result in false positives or negatives in forecasts.

One of the most significant limitations of geofencing is that it uses pre-specified boundaries, which might not be dynamic and adjust to changing terrain conditions. This could be solved through dynamic geofencing as a solution, which enables the updating of risk zones based on sensor data in real time. Enlarging the communication modes beyond geofencing—telecom towers, IoT networks, and satellite-based warning systems—are potential solutions that could enhance the scalability of the system.

V. Conclusion And Future Scope

Our study successfully established an artificial intelligence (AI)-driven landslide prediction model, showing machine learning's application for the effective assessment of hazard. Using geofencing and real-time visualization by means of ThingSpeak, the system forms the cornerstone of an automatic disaster surveillance model

But this geofence-based warning system has some limitations regarding range, flexibility, and applicability in real-world scenarios. One of the main issues is that geofencing in a predetermined area means that hazards outside the defined zone might not be detected. Dai et al. [16] mentioned that changes in terrain, modifying landslide-risk zones, and climate variability diminish the efficacy of static geofenced models. Also, real-time monitoring using sensors poses challenges in the form of network connectivity loss, sensor calibration faults, and delay in transmitting data

To bridge these constraints, subsequent studies need to extend the system beyond geofencing by incorporating multi-network transmission techniques. A potential enhancement is sending landslide warnings through telecom towers so that warnings can be disseminated over cellular networks using SMS, push notifications, or emergency alerts. Despite that, telecom-based alerting also has network-coverage challenges where remote areas may pose difficulties, and might demand multi-network backup via 2G, 4G, or satellite-based communication

Another promising strategy is the use of IoT-based Low-Power Wide Area Networks (LPWANs) like LoRaWAN and NB-IoT, which support long-range, low-power data transmission appropriate for distant landslide-prone areas. These networks enable efficient transmission of sensor-based risk data over large distances without the intervention of constant human monitoring.

Subsequent implementations must also consider integration with roadside facilities and vehicle communication networks. By embedding smart LED traffic signs, autonomous sirens, and V2X communication modules, pedestrians and vehicles in dangerous areas may receive real-time danger alerts as they enter unstable regions. [17]

The scope of this project in the future entails increasing the dataset of the AI model, incorporating increasingly varied environmental parameters, and optimizing adaptive learning to achieve higher prediction accuracy. Mechanisms for automated calibration of sensors should also be formulated to minimize errors due to environmental noise and hardware constraints [18]. In addition, the system may be supplemented by AI-based drones that carry geological scanning devices for real-time terrain inspection and landslide hazard mapping where physical sensors are not possible.

By embracing an approach that multi-layers the use of geofencing, telecom-based alarms, IoT networks, and AI-powered monitoring, this study has the potential to become a large-scale, internationally accessible early warning system. Through this hybrid method, landslide hazard assessments will be not only regional but also effective at large-scale hazard detection, ultimately minimizing casualty and infrastructure losses in landslide-endangered areas all over the globe.

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