



AI AND IOT BASED SENSOR DATA-POWERED DISASTER EARLY WARNING WITH MACHINE LEARNING OPTIMIZED RISK MANAGEMENT

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ABSTRACT:

The rising frequency of natural disasters, particularly landslides, flash floods, and cloud bursting events, underscores the pressing need for reliable real-time detection and early warning systems. This paper introduces a novel solution, termed the Pressure Sensor Data Powered Disaster Detection with ML Optimized Risk, which harnesses the power of IoT technology for effective landslide detection and alerting. By utilizing rain gauges and soil moisture sensors pressure and tiltometer, the system centralizes data collection through a control unit equipped with GSM and LoRawan communication modules, facilitating both local and remote connectivity. The data gathered is then sent to a cloud platform, where a machine learning algorithm processes it to assess risk levels based on dynamic thresholds and historical trends. In the event that conditions indicative of a landslide are identified, alerts are promptly disseminated to local authorities and vehicles through buzzers, relays, and messaging systems to ensure a swift evacuation and response. This proactive approach significantly bolsters disaster preparedness, accelerates response times, and ultimately contributes to the preservation of lives and infrastructure.

****Keywords:**** *Landslide detection, IoT, machine learning, environmental sensors, early warning system, GSM, LoRawan, disaster risk management*

I. INTRODUCTION:

Landslides rank among the most devastating natural disasters, particularly in mountainous regions such as Wayanad(Kerala) and Uttarakhand. These events are often triggered by heavy rainfall, soil erosion, deforestation, and unstable geological conditions. Given their unpredictable nature, early detection is vital for minimizing damage and safeguarding lives. Conventional warning systems may fall short due to delays and inaccuracies. To address these challenges, our project proposes an innovative landslide detection and alert system leveraging IoT sensors and machine learning methodologies.

The system persistently monitors environmental parameters, including soil moisture, ground tilt, vibration, temperature, and humidity. Sensors are strategically placed in areas susceptible to landslides and are linked to a central microcontroller. The data collected is processed locally and transmitted to the cloud via GSM or LoRawan modules, ensuring real-time data acquisition and communication, even in remote settings .To



improve predictive accuracy, our project incorporates a machine learning model trained on historical landslide data. It employs the Chi-Square statistical method to compare current readings against established threshold values and detect significant deviations. This strategy enables the identification of early indicators of potential landslides through the analysis of patterns within the environmental data. Upon detecting a risk, the system activates an alert mechanism, which includes a buzzer, relay control, and warning notifications sent to local authorities and vehicles.

This multi-channel alert system is designed to provide timely evacuation and effective response during emergencies. The project presents a practical, cost-effective solution for monitoring and preventing landslide disasters by merging real-time sensing technology with intelligent risk assessment.

Key objectives of this paper is Real-Time Monitoring, Efficient Alert Mechanisms, Accessibility and Inclusivity, Reliability in Challenging Conditions, Scalability and Cost-Effectiveness

2.Scope of the Work :

The aim is to establish a dependable, real-time landslide detection and alert system that integrates IoT, machine learning, and statistical analysis. It specifically targets regions at high risk for landslides flash floods due to heavy rainfall, unstable slopes, or frequent seismic activity. The heart of the system is continuous environmental monitoring using sensors that track factors such as vibration, soil moisture, and tilt, generating real-time data on ground movement and soil saturation—critical indicators for predicting potential landslides.

The hardware consists of a central control unit that serves as a data hub, collecting readings from the sensors. It utilizes GSM and LoRawan modules for data transmission over varying distances. GSM facilitates SMS communication with authorities and emergency responders, while LoRawan allows for long-range, low-power communication in remote locations. This setup guarantees ongoing data transfer and alert capabilities even in areas with limited mobile coverage. The system is designed for durability and energy efficiency, making it suitable for outdoor and off-grid use. On the software side, a machine learning algorithm is employed to identify patterns in sensor data indicative of landslide risk. This algorithm is augmented with Chi-Square statistical analysis, which validates the significance of any deviations in the sensor data. By correlating current sensor readings with established normal ranges, the Chi-Square approach ensures that the machine learning model responds only to relevant changes, enhancing accuracy and minimizing false alarms.

The paper also include the features a multi-level alert mechanism. Upon detection of risk, the system activates buzzers and relays for immediate on-site warnings, while simultaneously sending SMS alerts to relevant authorities, vehicles, or public systems. These alerts are timely and location-aware, facilitating swift responses and evacuations. Although the current emphasis is on landslides, the modular design allows for future modifications to address other disaster scenarios, including floods or earthquakes, with minimal adjustments to the hardware and software infrastructure. This adaptability makes the project a scalable and flexible solution for comprehensive disaster management efforts.

3.Internet of Things (IoT) in Landslide Detection System:

In our landslide detection system, the Internet of Things (IoT) is essential for gathering and transmitting real-time environmental data from a variety of sensors. These sensors track crucial factors like soil moisture, rainfall, temperature, humidity, and ground movement, all of which are vital for identifying the early



indications of a landslide. The data collected by these sensors is sent to a central processing unit, typically a microcontroller, for analysis and interpretation, enabling predictions about potential landslides.

Once the IoT sensors capture the data, it is relayed to a microcontroller for preliminary processing. Subsequently, this data undergoes analysis using machine learning algorithms to assess the likelihood of a landslide. A major advantage of incorporating IoT into this system is the real-time monitoring of environmental conditions, facilitating prompt responses and early warnings for local communities.

4.Real-Time Data Transmission and Alerts:

The IoT-based system not only captures and analyzes environmental data but also plays a crucial role in sending alerts to individuals within the impacted areas. When sensors identify values that surpass predefined thresholds—such as excessive soil moisture—the system automatically triggers an alarm and notifies the appropriate parties. These alerts can be disseminated through SMS, app notifications, or visual signals, such as flashing lights or alarms, ensuring accessibility especially in regions with limited connectivity or for those with hearing impairments.

In regions like Ooty, each village can deploy its own network of IoT sensors that relay data back to a centralized control room. This setup creates a tailored warning system, ensuring that each locality receives timely and relevant updates on landslide threats.

1.1 Data Monitoring and Analysis:By consistently tracking environmental factors with IoT devices, the system delivers instant alerts and accumulates data for analysis. Over time, evaluating patterns in soil moisture, rainfall, and temperature enables the refinement of machine learning models for landslide detection. This proactive method allows for the identification of potential landslide risks days or even weeks in advance, providing local authorities and residents ample time to prepare and evacuate if necessary.

5. METHODOLOGY:

The proposed system commences with Sensor Initialization, during which environmental sensors, including rain gauges, tilt sensors, humidity, and temperature sensors, are activated and set up for continuous monitoring. After initialization, the system advances to the Data Collection phase, where real-time data is collected from sensors strategically positioned in the field. This data is subsequently processed in the Data Processing stage, where initial threshold evaluations are performed. Specifically, if rainfall measures between 1mm and 20mm, tilt values exceed 20°, and humidity levels are above 60%, the data is deemed significant and initiates 24-hour real-time monitoring. Following this, the sensor nodes relay data to the central gateway, which aggregates information from multiple nodes. Upon successful data reception, the gateway establishes a network connection and forwards the processed sensor data to a cloud-based server for further analysis. Subsequent to this, the sensor nodes relay data to the central gateway, which is tasked with aggregating information from various nodes. Once the data is successfully received, the gateway initiates a network connection and forwards the processed sensor data to a cloud-based server for additional analysis. The system then conducts a secondary validation: if the tilt angle exceeds 45°, rainfall is between 5mm and 10mm, humidity is greater than 60%, and the temperature surpasses 25°C, the system recognizes a potentially dangerous situation.

This scenario triggers the activation of the alert mechanism, which encompasses a buzzer notification to alert local authorities or connected emergency systems. Furthermore, the flowchart features parallel decision branches designed to more proactively identify high-risk events. These branches independently assess for more critical or unusual values—such as rainfall ranging from 10mm to 15mm with a tilt exceeding 95°, or a tilt below 30° combined with high humidity and low temperature, thereby bypassing intermediate steps to directly trigger the buzzer notification system. This dual-path logic guarantees that the system remains responsive under diverse environmental conditions, enabling it to function in both progressive risk accumulation and sudden event detection modes. In summary, the methodology provides robust, real-time, and intelligent environmental monitoring focused on early disaster detection and prompt alert generation.

6. PROPOSED SYSTEM

The proposed system introduces an innovative approach to predicting and mitigating landslides by integrating machine learning algorithms with smart IoT devices. The system aims to provide an efficient and real-time solution to monitor, analyze, and predict landslide occurrences. Smart IoT sensors, strategically placed in landslide-prone areas, collect data on various environmental parameters such as soil moisture, rainfall intensity, ground vibrations, and slope stability.

This data is transmitted to a cloud-based platform, where advanced machine learning algorithms process and analyze it. The machine learning models are trained using historical and real-time data to identify patterns and provide accurate predictions of potential landslide events. The system utilizes supervised and unsupervised learning techniques to continuously enhance the prediction accuracy and adapt to changing environmental conditions.

To ensure data integrity and seamless communication, the system employs a robust and secure communication protocol between IoT devices and the cloud. The system also integrates real-time alert mechanisms, sending notifications to concerned authorities and local communities in case of predicted landslide risks. These alerts are delivered through multiple channels such as mobile apps, SMS, and email, ensuring timely evacuation and disaster management. Furthermore, the system features a user-friendly interface for visualizing data and predictions, enabling stakeholders to monitor risk levels and take informed decisions.

Access control measures are implemented to ensure only authorized personnel can access the system, maintaining data privacy and security. This proposed system not only enhances landslide prediction but also contributes to proactive disaster prevention, ultimately safeguarding lives and property.

7. Mathematical Explanation:

Chi-Square Test Formula: $\chi^2 = \sum [(O_i - E_i)^2 / E_i]$

where O_i : Observed sensor reading frequencies, E_i : Expected frequencies under normal conditions. The Chi-Square test determines whether variations in sensor data are statistically significant.

Purpose in Model: Identifies sensor variables strongly associated with disaster events. Helps reduce false alarms.

Triggers alerts when statistically significant anomalies are

detected. If the calculated value is less than the table for 10% significant level then there is no risk that is normal and if

calculated value is greater than table value then abnormal the table value is if calculated $\chi^2 > \text{Table } \chi^2$

So H_1 is Accepted, changes are happening

8.BLOCK DIAGRAM

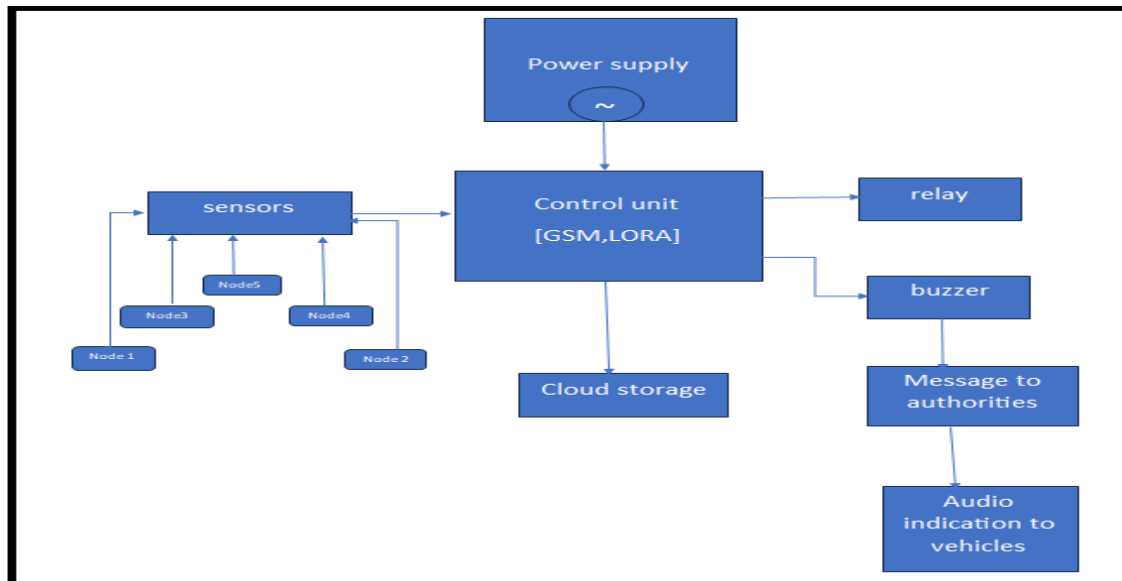


Fig.I.-Block Diagram

9. FLOWCHART:

The flow chart outlines the systematic process of the project, starting with Sensor Initialization, where environmental sensors are initialized and prepared for data transmission. The next step is Data Collection, where data is gathered from sensors placed at various nodes. This data then undergoes Data Processing, where continuous monitoring occurs. If no risks are detected, the system labels the data as NORMAL; otherwise, it is flagged as ABNORMAL. The processed data is then sent to the Control Unit, which utilizes technologies like GSM or LoRa for communication. From there, the data is stored in Cloud Storage for further analysis and record-keeping. In case of abnormal data, the system triggers Messages to Authorities (phones or computers) and provides Audio Indications to Vehicles to alert them of potential risks. The process concludes with the END of the cycle, ensuring a seamless and efficient monitoring and alert system

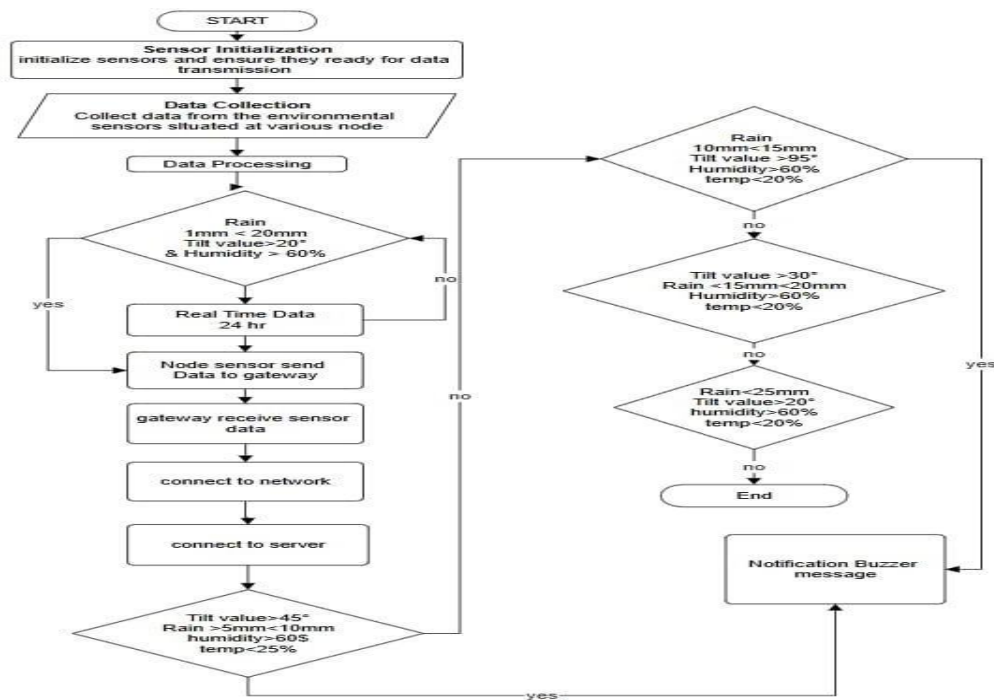


Fig.II-Flow Chart

10. SYSTEM SPECIFICATION

1. Real-Time Data Collection:

- The system shall continuously collect environmental data from IoT sensors, including soil moisture, rainfall intensity, temperature, and humidity.
- Data shall be transmitted to a central processing unit in real-time for analysis.

2. Land slide Prediction:

- The system shall employ machine learning algorithms to analyze sensor data and predict potential landslides.
- Predictions shall be based on predefined thresholds and historical data patterns.

3. Multi-Level Alert System:

The system shall generate three levels of alerts: **Green(Normal)**, **Orange (Potential Risk)**, **Red(Imminent Risk)**. Alerts shall be triggered automatically when sensor values exceeds thresholds values.

- **Alert Dissemination:** The system shall send alerts via SMS, mobile app notifications, and visual/auditory signals (e.g., flashing lights, alarms).

11. TECHNICAL SPECIFICATIONS:

1. Sensor Specifications:

- Soil Moisture Sensor: Measurement Range: 0–100% volumetric water content. Accuracy: $\pm 3\%$.
- Rainfall Sensor: Measurement Range: 0–200 mm/hr. Resolution: 0.2 mm.
- Temperature/Humidity Sensor: Range: -40°C to 80°C (temperature), 0–100% humidity). Accuracy : $\pm 0.5^{\circ}\text{C}$ (temperature), $\pm 2\%$ (humidity).

2. Communication Protocols:

- IoT devices shall use MQTT for light weight, real-time data transmission.
- GSM modules shall ensure connectivity in areas with limited internet access.

3. Cloud Platform:

- AWS IoT Core shall be used for device management and data ingestion.
- Machine learning models shall be deployed using AWS Sage Maker.

12. DATA ANALYSIS:

12.1. Wayanad Land slide–Real Data Analysis: The Wayanad landslides on July 30, 2024, were among the most devastating in Kerala's history, resulting in significant loss of life and property. Here's a detailed overview of the environmental conditions leading up to the disaster, including rainfall, temperature, humidity, and terrain factors.

12.2. Rainfall Patterns: In the 48 hours preceding the landslides, the region experienced an extraordinary 572 mm of rainfall, with 200 mm falling in the first 24 hours and 372 mm in the subsequent 24 hours. This deluge accounted for approximately 6% of Wayanad's annual rainfall, occurring within just a few hours. Specific are as on July 30 recorded Viyatri–280 mm, Mananthavady–200 mm, Ambalavayal –140 mm, Kupady–122 mm, These values far exceeded the IMD's threshold for "extremely heavy rainfall" (>204.4 mm/day).

12.3. Temperature and Humidity : In the two weeks leading up to the landslide (July 15–29), Wayanad experienced temperatures ranging between 22.8°C to 33.2°C . On July 29, the day before the landslide, the maximum temperature was 33.2°C . While specific humidity data isn't available, high temperature combined with heavy rainfall likely caused high humidity and saturated soil, which are key land slide triggers.

12.4. Terrain and Slope Stability: The land slide originated at an elevation of 1,544 meters. It raveled around 7 km. Estimated speed: 57 m/s (205 km/h) classified as "extremely rapid" by the Geological Survey of India. Affected villages included, Punjirimattom, Mundakkai, Chooralmala, Vellarimala. These are located in the Western Ghats, a landslide-prone hilly region.

13. Climatic Influences:

Climate change has made single-day monsoon downpours in Wayanad ~10% heavier. Arabian Sea warming has triggered deeper cloud formations, leading to intense rain over short periods. This climatic shift significantly increased the land slide risk in regions like Wayanad. The 15-Day Preceding Condition Summary between



July 15 to 29, rainfall was below average most days. On July 29, only 9 mm of rain was recorded (about 73% below normal). On July 30, there was a sudden and massive spike (up to 280 mm in some areas).

This abrupt surge in rainfall combined with already moist soil, steep terrain, and hot temperatures led to slope failure and massive landslides.

Uttarakhand Landslide-Real Data (February 7, 2021) Temperature: Before the Landslide (January 2021) average Temperature: Region recorded the warmest January in six decades. Chamoli temperatures ranged between 10°C to 15°C. By February 6, temperature rose to around 17°C. On February 7, 2021 Maximum temperature recorded: Around 16°C to 18°C. The sharp rise caused rapid snow melt.

Rainfall/ Snowfall:

Before the Landslide: Minimal rain fall in January 2021, Heavy snow fall between February 3–5, approx 0.58 mm. Rapid snow melt followed due to increased temperature, on February 6–7: No rainfall, but significant snow melt occurred.

Humidity: Before the Landslide (Feb 3–6): Humidity increased due to melting snow. Relative humidity was around 80% to 85%. February 7, Humidity levels were around 75% to 80%.

Terrain and Tilt (Geological Factors): No direct tilt sensor data available. Rock and ice mass measuring Around 400 mm x 700 mm x 150 mm detached. The mass fell approximately 1800 meters, triggering the Disaster. The terrain was unstable due to melting glaciers and snow.

Summary Table: Date before Landslide (January 2021) Temperature: 10°C - 15°C Rainfall/ Snowfall: Minimal rain, snow (Feb 3–5)-58 mm Humidity, 70% - 80% Terrain: Snow accumulation, unstable. February 6, 2021, Temperature 17°C Rainfall/Snowfall, Rapid snow melt Humidity: 80% Terrain: Unstable, prone to slide. February 7, 2021 (Event day) Temperature, 16°C - 18°C Rainfall/Snowfall: No rainfall, continued melt, Humidity: 75% - 80% resultant Landslide occurred

14. Conclusion

Landslides pose a significant threat to hilly and mountainous regions, causing loss of life, infrastructure damage, and economic setbacks. Traditional landslide detection systems often fail to provide real-time, accurate, and actionable warnings, leaving communities vulnerable. This paper addressed these challenges and solutions by developing an AI and IoT-based Landslide Monitoring and Machine Learning-Enhanced Prediction System, which integrates real-time sensor data, cloud computing, and intelligent algorithms to improve early warning capabilities to save life and prosperity.

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