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Solar-Powered IoT-Based Landslide Early Warning System for Remote and High-Risk Areas

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ABSTRACT

Landslides pose a significant threat to human safety and critical infrastructure, particularly in remote and high-rainfall regions. In these areas, continuous monitoring is difficult to sustain and reliable access to power is often limited. This paper presents the development and experimental evaluation of a solar-powered landslide early warning system (S-LEWS) that combines soil moisture and ground vibration sensing with Internet of Things (IoT) technology. An ESP32 microcontroller is employed for real-time data acquisition and slope condition assessment, classifying risk levels into safe ($S < 40\%$), warning ($40\% \leq S < 70\%$), and danger ($S \geq 70\%$ or vibration detected) states using predefined threshold criteria. Simulation and prototype-based testing confirmed accurate and repeatable alert responses across all evaluated scenarios, with ground vibration detection prioritized to ensure immediate danger alerts regardless of soil moisture conditions. The system provides hybrid sensing warning outputs, including visual indicators, an audible alarm and wireless notifications via Telegram. Energy autonomous operation is achieved through a solar photovoltaic (PV) module integrated with battery storage, enabling continuous day-and-night functionality without reliance on grid power. The findings demonstrate that S-LEWS operates reliably and show strong potential for sustained landslide risk monitoring in resource-constrained environments.

1. INTRODUCTION

Landslides are among the most destructive natural disasters observed globally. These events are particularly prevalent in tropical and mountainous regions, where intense rainfall, steep inclines, and weathered soil structures create favourable conditions for their occurrence. The rapid expansion of urbanization and infrastructure development into high-risk zones further exacerbates the impact of landslide events, leading to substantial social and economic losses. Over the past decades, landslides have affected more than 4.8 million individuals worldwide, tragically claiming over 18,000 lives. Analysis of the spatial distribution of landslides indicates that Southeast Asia is especially vulnerable to such hazards. For instance, a single,

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devastating incident in the region in 2025 resulted in over 1,140 fatalities (World Health Organization, 2026).

Conventional landslide monitoring methods often rely on large-scale instrumentation such as inclinometers, extensometers and geotechnical monitoring stations (Hobbs et al., 2020). While these systems provide high accuracy, they are expensive, energy-intensive and require skilled maintenance, making them impractical for deployment in rural and remote areas (Mugnai et al., 2023). This has led to limited deployment due to critical infrastructure sites rather than community-level monitoring. As a result, many communities in landslide-prone areas remain unmonitored despite facing higher vulnerability. From an academic research perspective, numerous studies have extensively investigated the use of wireless sensor network technologies with embedded platforms for landslide detection. Early research efforts primarily concentrated on deploying multi-sensor systems that monitor key parameters such as soil moisture, ground vibration, displacement, tilt, rainfall and other environmental factors to identify early indicators of slope instability (Giorgetti et al., 2026; Syafiq et al., 2013; Wu et al., 2017). A variety of communication standards have been adopted, such as ZigBee for short-range low-power networking GSM/GPRS for wide-area connectivity and LoRa for long-range, energy-efficient transmission in remote environments (Bhangale et al., 2022).

Recent advances in low power microcontrollers, sensor technologies and wireless communication have enabled the development of compact IoT-based monitoring systems (Amirthavarshini et al., 2026; Gupta & Satyam, 2024). These systems are commonly deployed on embedded hardware platforms such as Raspberrypi, MicaZ, TelosB, Arduino and WaspMot microcontrollers which are selected for their ability to deliver sufficient processing capabilities while maintaining low energy demands (Thirugnanam et al., 2022). Kumar (2022) demonstrated a real-time detection system by combining the micro-electro-mechanical system (MEMS) accelerometers and soil moisture sensing with GSM-based alert mechanisms, while Srinidhi et al. (2025) and Bhadre (2024) applied ESP-based multi-sensor frameworks integrated with cloud platforms for remote visualization and notification. However, these approaches rely on complex sensor arrays, external databases or continuous data transmission that increase system complexity and limit long-term autonomous operation in resource-constrained or off-grid locations. These observations highlight the need for simplified, energy-autonomous landslide early warning systems that prioritise critical sensing parameters while maintaining reliable and timely alert delivery.

Soil moisture and ground vibration are well acknowledged in the literature as dependable preliminary indicators of slope instability. Increased water content in the soil reduces soil strength and raises the pore water pressure. Unusual ground vibration could mean that the ground is moving below the surface before the slope fails. However, many reported low-cost landslide monitoring systems rely on single-parameter sensing or lack autonomous power capabilities, which can result in delayed alerts, increased false alarms, or restricted operational lifetime. Another significant limitation of existing systems is the absence of priority-based decision logic. In practical scenarios, sudden ground vibration or slope movement should immediately trigger high-risk alerts, regardless of soil moisture conditions. Systems that treat all monitored parameters with equal priority may fail to respond promptly to rapid failure mechanisms. Recent studies have integrated IoT platforms with cloud computing and machine-learning models to forecast landslide events using historical and real-time sensor data. For example, Singh and Anurag (2024) proposed a comprehensive IoT–cloud architecture employing LSTM and GRU models to predict landslide risk levels based on hydrological, meteorological, and geographical parameters, achieving high classification accuracy across multiple threat categories. However, such approaches focus primarily on predictive modelling rather than real-time detection and immediate alerting.

Therefore, to address these limitations, this paper proposes a solar-powered IoT-based landslide early warning system (S-LEWS) integrating dual-parameter sensing with a priority-based risk classification algorithm. The system is designed for autonomous operation in remote environments and delivers real-time alerts through both local and wireless channels. This paper makes two main contributions: (i) the

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development of an energy-autonomous, dual-parameter IoT-based landslide early warning framework integrating soil moisture and vibration sensing, and (ii) the implementation of a priority-based real-time decision algorithm with experimental and quantitative performance validation, enabling reliable and rapid danger alerts under resource-constrained conditions.

2. METHODOLOGY

2.1 System architecture

Prior to designing the S-LEWS prototype, simulations were performed using Wokwi and Proteus platforms to validate the decision logic and alert behaviour. Hardware experiments were conducted using a fabricated prototype under controlled test scenarios representing dry soil, saturated soil and vibration-induced conditions. The entire system is powered by a solar PV module with battery energy storage that allows autonomous, continuous operation in remote landslide-prone environments. Fig. 1 depicts the system architecture of the proposed solar-powered IoT-based landslide early warning system. The system integrates a soil moisture sensor and a vibration sensor to monitor gradual slope saturation and sudden ground movement, respectively. The ESP32 microcontroller functions as the brain of S-LEWS that continuously processes the sensor data and performing signal normalization, comparison of threshold and risk classification by deploying a priority-based decision-making algorithm. At any state of soil moisture level, vibration detection will immediately trigger a high-risk (DANGER) state. Visual indicators such as liquid crystal display (LCD) and LEDs as well as an audible buzzer are installed for on-site warning. On the other hand, ESP32 communicates wirelessly with a smartphone via a Telegram-based IoT platform, enabling real-time notification.

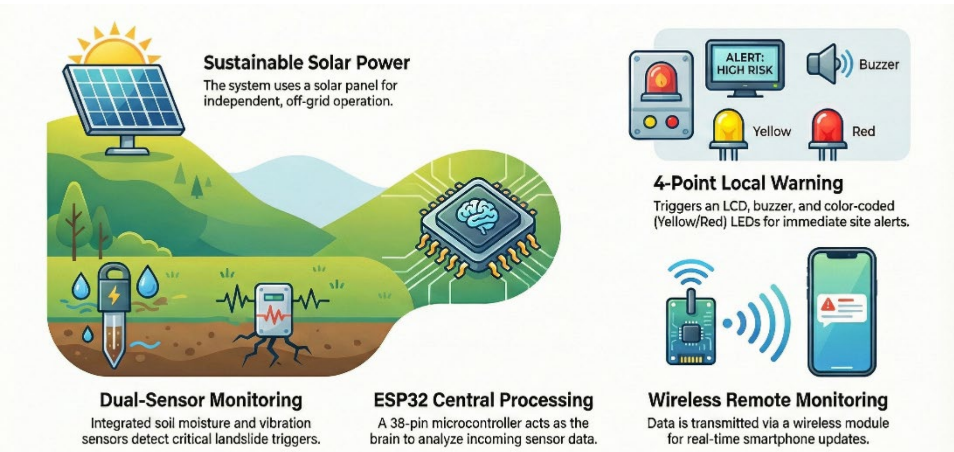

Fig. 1. S-LEWS system architecture

Since the S-LEWS designed for environmental monitoring and alert generation. The system is structured into five (5) distinct layers: Sensing, Processing, Decision, Alert, and Power as described in Table 1. The layers describe the S-LEWS modular design, scalability and ease of maintenance. The reason for choosing the ESP32 is because of its low energy usage, built-in Wi-Fi and its ability to be used in IoT applications. For the sensor layer, two (2) types of sensors are used, namely soil moisture and vibration sensors. The deployment of these sensors assists minimizing long-term drift and corrosion, while enabling the detection of ground movement through digital signal triggering. To ensure continuous operation during laboratory trials, the S-LEWS prototype is powered by a compact solar PV module (nominal 3V) with a rechargeable battery.

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Table 1. S-LEWS system layers

Layers	Description
Sensors	Soil Moisture Sensor and Vibration Sensor used to capture relevant environmental information that are then fed into processing layers.
Processor	ESP32 microcontroller as a brain of S-LEWS system that is responsible for data processing and communication.
Decision making	Apply threshold-based risk classification with priority logic rules.
Alert	Provides feedback to the user based on the decisions made. It utilizes LED indicators, buzzer and telegram notifications as an alert mechanism
Power	Provides a reliable and sustainable power source for the entire system. It consists of a solar PV module with battery energy storage

Fig. 2 illustrates the operational sequence of the S-LEWS. The system begins with initialize the input data, wireless connection setup and continuous monitoring loop by ESP32. Soil moisture data are acquired in real time and the levels are evaluated based on the predefined thresholds classified as safe, warning and danger states. These states will activate corresponding visual and audible alerts. Concurrently, any detection of real time ground vibration will immediately trigger a danger alert regardless of soil moisture level. The system will restart the monitoring loop after the alert activation to ensure continuous real time operation.

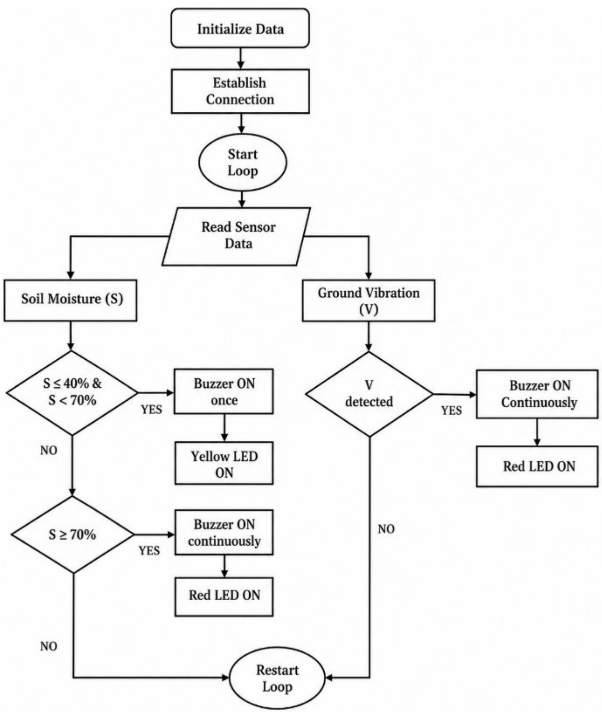

Fig. 2. Flow Chart of the S-LEWS

Table 2 lists the sensors and components used in the S-LEWS along with their measured parameters and functional roles. The components are carefully selected to ensure the system is able to support the real time monitoring and alert generation for critical landslide indicators with minimal system complexity.

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Table 2. Sensors and alerting components used in the S-LEWS architecture

No.	Sensor / Component	Measured Parameter	Function
1	Capacitive soil moisture sensor	Soil moisture (saturation)	Monitors gradual soil saturation associated with rainfall infiltration
2	Vibration sensor	Ground vibration	Detects sudden subsurface movement and triggers priority alerts
3	ESP32 microcontroller	Sensor signal acquisition and processing	Performs data acquisition, normalization, risk classification, and communication
4	LCD	System status and risk level	Displays real-time system state locally
5	LED indicators (yellow, red)	Alert status	Provides visual warning for warning and danger states
6	Buzzer	Audible alert	Generates audible alarms during elevated risk conditions

2.2 Soil moisture signal normalization

The raw analog capacitive soil moisture readings are normalized to represent the soil saturation percentage. The purpose of linear normalization is to ensure the uniform relationship between soil moisture and sensor output within the operating range. Eq. (1) shows the linear normalization applied for the S-LEWS system.

$$Soil(\%) = \frac{S_{raw} - S_{dry}}{S_{wet} - S_{dry}} \times 100 \quad (1)$$

Where the S_{raw} represent the sensor reading obtained by the ESP32 analog-to-digital converter (ADC), S_{dry} refers to the value measured under dry soil conditions while S_{wet} is the value obtained when the soil is fully saturated. The soil moisture is expressed in percentage form to simplify the risk classification thus allowing the thresholds with intuitive repeatability. In this study, the soil saturation thresholds are classified as safe, warning and high-risk conditions that depends on the soil moisture levels.

2.3 Ground vibration detection

To ensure rapid response and minimize the computational complexity, the binary representation is chosen for the ground vibration sensor. The presence or absence of any abnormal ground vibration is defined in eq. (2) below.

$$V = \begin{cases} 1, & vibaration\ detected \\ 0, & no\ vibration\ detected \end{cases} \quad (2)$$

The vibration sensor output is continuously monitored and any detected vibration event immediately triggers a high-risk condition within the decision algorithm. This design reflects practical landslide behaviour, where sudden ground movement can potentially lead to catastrophic failure even when soil moisture levels are below critical thresholds. For this reason, vibration detection has been assigned a higher priority than soil moisture levels in the risk classification logic. By combining continuous soil moisture monitoring with vibration detection, the proposed system captures both gradual slope weakening and sudden ground movement, thus improving the reliability and responsiveness of the landslide early warning mechanism.

2.4 Risk classification

The landslide *Risk (R)* level is determined using the decision logic as shown in eq. (3). This formulation prioritizes vibration occurrences over gradual soil moisture increase. This indicates real-world landslide behavior where sudden ground movement may lead to catastrophic failure.

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$$Risk\ (R) = \begin{cases} SAFE, & S < 40\%, and\ V = 0 \\ WARNING, & 40\% \leq S < 70\%, and\ V = 0 \\ DANGER, & S \geq 70\%\ or\ V = 1 \end{cases} \quad (3)$$

To apply the risk classification method in real time, a decision-making algorithm was embedded directly into the S-LEWS. This algorithm integrates normalized soil moisture and ground vibration measurements to determine the system risk state based on predefined thresholds and priority rules. Vibration detection is given the highest priority to enable immediate hazard classification, independent of soil moisture levels. Algorithm 1 presents a step-by-step summary of the decision logic implementation.

Algorithm 1 Priority-Based Risk Classification and Alerting in S-LEWS

Input: Soil moisture sensor reading ADC_raw, vibration indicator V ∈ {0,1}, calibration constants ADC_dry and ADC_wet. Algorithm 1: Priority-Based Risk Classification and Alerting (S-LEWS)

Input: soil moisture S (%), vibration V ∈ {0,1}
Output: local alerts (LED/buzzer/LCD), remote alert (Telegram)

```
Initialise peripherals (LCD, LEDs, buzzer), Wi-Fi and Telegram bot
loop forever:
    Read ADCraw from soil moisture sensor; compute S (%) using calibration
    Read vibration sensor; set V = 1 if vibration detected else 0
    if (V = 1) OR (S ≥ 70%) then
        state ← DANGER
        Activate red LED + continuous buzzer
        Send Telegram "DANGER" notification (rate-limited)
    else if (40% ≤ S < 70%) then
        state ← WARNING
        Activate yellow LED + intermittent/one-beep buzzer
        Send Telegram "WARNING" notification (rate-limited)
    else
        state ← SAFE
        Keep alerts off (monitoring mode)
    end if
    Update LCD with S, V and state
end loop
```

2.5 Power autonomy model

To ensure continuous and autonomous operation in remote and off-grid environments, the S-LEWS is designed such that the daily energy harvested from the PV module is sufficient to supply the system load and associated conversion losses. Energy autonomy is achieved when the following condition in eq. (4) is satisfied.

$$E_{PV} = E_{load} + E_{loss} \quad (4)$$

Whereby E_{PV} represents the daily electrical energy generated by the solar photovoltaic panel, E_{load} refers to the total daily energy consumption of the system, and E_{loss} accounts for energy losses arising from power conversion, battery charging and discharging inefficiencies and voltage regulation. The proposed power autonomy model provides simple yet effective basis for scaling the solar PV and battery capacity based on the site location, load cycle and solar availability.

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3. RESULTS AND DISCUSSION

In order to validate the real-time operation of S-LEWS under different risk conditions, the hardware prototype has been developed as shown in Fig. 3. The prototype consists of ESP32 microcontroller, vibration sensors, soil moisture, audible buzzer, LCD module and visual indicators (yellow and red LEDs). The LCD equips real-time feedback on the S-LEWS system state that indicates safe, warning or danger conditions determined by the sensor inputs and the priority-based decision logic declared. Warning conditions activate the yellow LED with blinking indication while danger conditions trigger the red LED and continuous alarm, conforming true execution of the warning mechanism. These observations confirm the functional integration of hardware and firmware required for continuous monitoring and immediate alert generation.

Fig. 3. S-LEWS prototype

Fig. 4 continues to demonstrates the S-LEWS remote alerting capabilities via Telegram notifications. The developed system is capable of transmitting warning and danger notifications that include real-time soil moisture readings and vibration status once predefined risk thresholds are exceeded. Warning notifications are generated when soil moisture reaches the threshold range under normal vibration conditions. In contrast, danger notifications are immediately triggered when vibration is detected, even if the soil moisture remains below the critical value. Repeated notifications observed during sustained vibration events confirm continuous monitoring and timely message delivery rather than single event triggering. This remote notification mechanism enables off-site users to receive situational awareness in near real time, thereby extending the effectiveness of the early warning system beyond local, on-site alerts.

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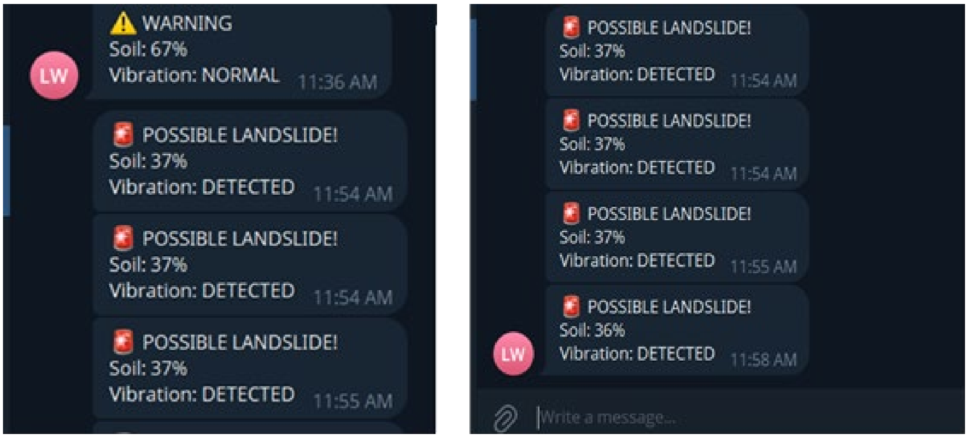

Fig. 4. S-LEWS telegram notification

Table 3 summarizes the experimental validation of the S-LEWS alert response under various soil moisture and vibration conditions. In the absence of vibration and at soil moisture levels below 40%, the system classifies the condition as *safe*, with only minimal alert indications. As soil moisture increases to 70%, a *warning* state is activated, reflected by a yellow LED and an intermittent audible signal, indicating an elevated but non-critical risk level. The system transitions to a *danger* state when soil moisture reaches or exceeds 70%, even in the absence of vibration, triggering a red LED and a continuous alarm. Importantly, any detected ground vibration immediately results in a *danger* classification, regardless of the soil moisture percentage, thereby confirming the effectiveness of the priority-based decision logic. Overall, the results demonstrate consistent and accurate alert activation across all tested scenarios.

Table 3. Alert response validation

Soil Moisture (%)	**Vibration**	**Risk Level**	**Alert Output**
< 40	No	SAFE	Yellow LED, single beep
40–70	No	WARNING	Yellow LED, intermittent
≥ 70	No	DANGER	Red LED, continuous
Any	Yes	DANGER	Red LED, continuous

The end-to-end S-LEWS alert latency was experimentally assessed under different two (2) trigger conditions namely soil moisture threshold crossing and ground vibration detection. Alert response latency is a crucial performance indicator in landslide early warning systems as prolong delays may substantially delay the evacuation procedures and risk mitigation. In this study, the latency measurement was conducted using internal firmware timestamps within the ESP32 microcontroller. The system recorded the time at which the sensed parameter first exceeded its predefined threshold using the built-in millisecond resolution system clock. Fig. 5 illustrates the experimental alert latency with 95% confidence intervals. The results show that vibration triggered alerts respond faster than soil moisture triggered alerts. This confirms the efficiency of the priority-based decision logic that overrides sequential threshold evaluation when vibration is detected. The average latency for vibration-triggered alerts was approximately 0.6 s, while soil moisture–triggered alerts exhibited a higher average latency of approximately 1.2 s. Across all test scenarios, the maximum observed latency did not exceed 1.31 s.

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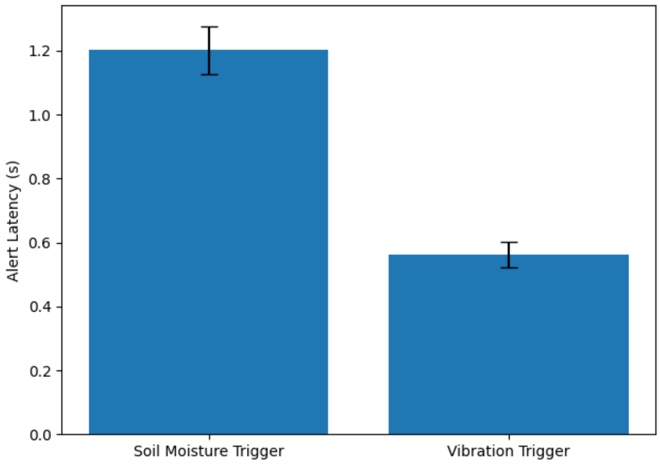

Fig. 5. S-LEWS alert response latency

Fig 6 depicts the time-dependent variation of normalized soil moisture observed during the experimental testing. A gradual increase of soil moisture indicates progressive water infiltration which is consistent with conditions experienced during prolong precipitation. The predefined warning (40%) and danger (70%) thresholds for landslide risk classification are denoted by two (2) horizontal dashed lines. During the initial stages, soil moisture remains below 40%, representing a safe operational state. When moisture content exceeds the 40% threshold, the system enters a warning state, reflecting an elevated risk of slope instability. Further increases in soil moisture beyond 70% activate the danger state. The results validate the system's ability to continuously monitor soil moisture in real time and accurately detect threshold crossings required for early warning activation.

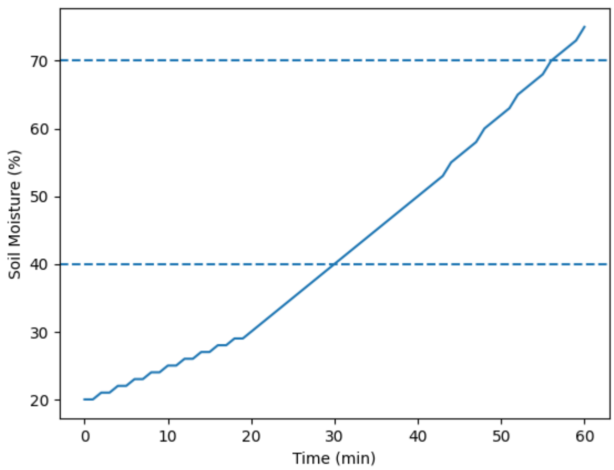

Fig. 6. Soil moisture variation with risk thresholds

The dynamic progression of the system alert under simultaneous soil moisture and vibration inputs is presented in Fig 7. Initially, the system remains in a safe state while soil moisture is below the warning threshold. As soil moisture increases and exceeds the 40% threshold, the alert state transitions to warning state, indicating elevated landslide risk. A further increase in soil moisture alone would normally be

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required to reach the danger state. However, at approximately 85 s, a ground vibration event is detected. The system immediately changes to the danger state regardless of the current soil moisture level. These findings substantiate the effectiveness of the priority driven decision logic, where vibration events take primacy over soil moisture thresholds.

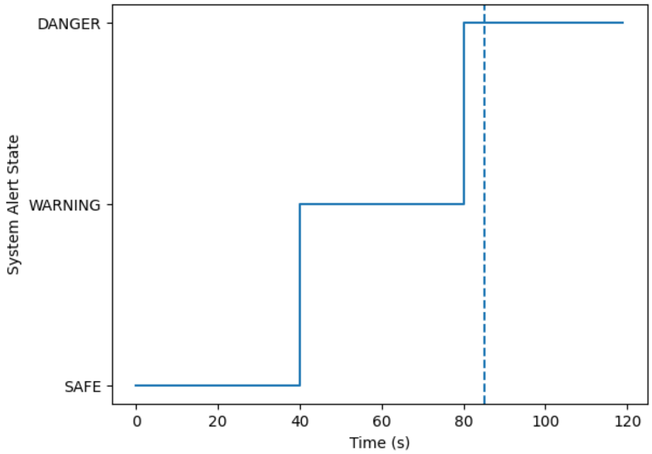

Fig. 7. Alert Response timeline with priority-based vibration detection

4. CONCLUSION

This paper presented and experimentally validated S-LEWS, a solar-powered IoT-based landslide early warning system. The proposed system combines dual-parameter sensing with a priority-based classification algorithm for improved reliability and faster response. The implemented algorithm assigns higher precedence to ground vibration, ensuring immediate transition to the DANGER state when rapid slope movement is detected, regardless of soil moisture conditions. Experimental validation demonstrated successful alert activation across all predefined scenarios, including safe, warning, and danger classifications. Measured response times indicated that vibration triggered alerts were activated rapidly compared to moisture-based transitions thus reflecting the intended priority logic embedded in the system. In all test scenarios, the maximum observed latency remained within 1.31 s, demonstrating consistent near real-time responsiveness. Local notification through visual indicators and audible alarms functioned reliably, while wireless communication enabled real-time remote monitoring. The solar PV module and battery storage subsystem operated consistently throughout testing thus supporting autonomous deployment in off-grid and landslide prone environments.

Despite these promising results, several limitations need to be recognized. The S-LEWS was assessed under controlled laboratory and prototype testing conditions. The system has not yet undergone long-term field deployment under diverse soil types, rainfall intensities and environmental conditions. Second, vibration detection is implemented as a binary indicator, which prioritises rapid response but does not capture vibration magnitude or frequency characteristics that may further improve risk discrimination. Finally, the present communication framework relies on Wi-Fi connectivity, which may limit coverage in certain remote locations. Future work will move beyond controlled testing toward outdoor field trials under real slope conditions. These efforts may include integrating additional sensing modalities such as rainfall and tilt sensors, refining vibration signal analysis and adopting long-range communication technologies to strengthen system robustness and improve scalability in wider deployments.

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6. CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

7. AUTHORS' CONTRIBUTIONS

Nur Iqtiyani Ilham: Writing – original draft, methodology, conceptualization, visualization, formal analysis, resources, supervision; **Marznesha Anak Lawrence**: Analysis, software, validation, investigation, formal analysis, resources; **Mashitah Hussain**: Project administration, writing –review and editing; **Wan Suhaifiza W.Ibrahim**: Writing –review and editing

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