International Journal of Engineering & Extended Technologies Research (IJEETR)

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802093

Adaptive AI-Lora Early-Warning System for Remote Disaster-Prone Areas

Dr.R.Sudha, Pavithraa.S, Ramyaprabha.M, Mirudhuladevi.B, Yazhini Yadav.R

Associate Professor, Department of Electronics and Communication Engineering, Sri Shakthi Institute of Engineering and Technology, Coimbatore, Tamil Nadu, India

Department of Electronics and Communication Engineering, Sri Shakthi Institute of Engineering and Technology, Coimbatore, Tamil Nadu, India

Publication History: Received: 25.02.2026; Revised: 20.03.2026; Accepted: 25.03. 2026; Published: 28.03.2026.

ABSTRACT: Remote and disaster-prone regions frequently experience failures in conventional communication infrastructure during emergency situations, resulting in delayed warnings and increased loss of life and property. To address this challenge, this paper presents an adaptive AI-driven LoRa-based early-warning system designed to operate reliably in infrastructure-deficient environments. The proposed system employs distributed sensor nodes to continuously monitor critical environmental parameters, including flood level, rainfall, soil moisture, seismic vibration, fire, and gas leakage. Upon detecting abnormal conditions, sensor data is transmitted using a low-power long-range (LoRa) communication network to a central gateway. An embedded AI-based decision module processes multi-sensor data to classify disaster type and severity and generates context-aware safety instructions rather than generic alerts. The system operates on battery power with optional solar support, ensuring continuous functionality during power outages. Experimental evaluation demonstrates reliable long-range communication, low power consumption, and timely generation of actionable alerts. The proposed solution is suitable for large-scale deployment in rural and remote regions for effective disaster management and early warning.

KEYWORDS: Disaster management, LoRa communication, Internet of Things, Early warning system, Artificial intelligence, Remote monitoring

I. INTRODUCTION

In many disaster-prone areas, conventional communication systems based on cellular networks or internet connectivity become unreliable or completely unavailable during emergencies due to power outages, network congestion, and physical damage. As a result, warnings are often delayed, leading to avoidable loss of life and property. Furthermore, traditional early-warning systems commonly rely on fixed threshold-based mechanisms that generate generic alerts without providing actionable or situation-specific guidance to affected communities.

Recent advancements in low-power wide-area networks (LPWAN) and artificial intelligence (AI) have enabled the development of more resilient disaster monitoring solutions. LoRa technology provides long-range communication with low power consumption and robust performance in harsh environments, making it suitable for remote and off-grid monitoring applications. Although AI-based approaches can improve disaster detection accuracy by analysing sensor data patterns and assessing severity levels, most existing solutions depend on cloud-based processing and continuous internet connectivity. To address these limitations, this paper proposes an adaptive AI-driven LoRa-based early-warning system that integrates multi-sensor monitoring with localized intelligent decision-making to deliver context-aware safety instructions in disaster-prone remote regions.

II. RELATED WORK

A. LoRa-Based Disaster Monitoring Systems

LoRa technology has been widely adopted in disaster monitoring applications due to its ability to provide long-range communication with minimal power consumption. Several studies have proposed LoRa-based systems for flood monitoring, landslide detection, fire alerting, and earthquake sensing. These systems typically employ distributed sensor nodes that collect environmental data and transmit it to a central gateway or monitoring station. Experimental results reported in the literature demonstrate reliable communication over several kilometres and extended battery life, making LoRa suitable for continuous monitoring in rural environments.

However, most LoRa-based disaster monitoring systems rely on predefined threshold values to trigger alerts. While effective in simple scenarios, threshold-based systems are prone to false alarms and lack adaptability to dynamic environmental conditions. Additionally, these systems generally transmit raw sensor data or basic alerts without interpreting the information to provide actionable guidance

B. AI-Based Disaster Detection Systems

Artificial intelligence and machine learning techniques have been increasingly explored to enhance disaster detection accuracy. AI-based systems analyze historical and real-time sensor data to identify disaster patterns and predict severity levels. These approaches reduce human intervention and improve decision-making efficiency. Despite their advantages, most AI-assisted disaster management systems depend heavily on cloud computing platforms and internet connectivity for data processing and storage. This dependency limits their usability during disasters when communication infrastructure is compromised.

The proposed system combines the strengths of both approaches by integrating LoRa-based communication with embedded AI-driven decision-making, enabling intelligent, decentralized disaster monitoring without reliance on external networks.

III. SYSTEM ARCHITECTURE AND METHODOLOGY

C. Overall System Architecture

The proposed system adopts a three-tier architecture comprising distributed sensor nodes, a LoRa-based wireless communication network, and a central gateway with an embedded AI-driven decision module. This architecture is designed to enable reliable disaster monitoring and alert dissemination in remote and infrastructure-deficient regions.

Sensor nodes are deployed across disaster-prone locations to continuously monitor environmental parameters such as rainfall, soil moisture, water level, vibration, fire, and gas leakage. Each node performs preliminary data evaluation to detect abnormal conditions while reducing unnecessary data transmission. The collected data is transmitted to the gateway via a low-power long-range LoRa network, where it is processed by the AI-based decision module to determine disaster type and severity. Based on the analysis, context-aware alerts and safety instructions are generated and delivered through local visual and audio indicators, ensuring timely warnings even in the absence of internet or cellular connectivity..

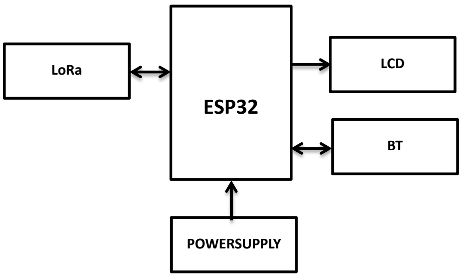


Fig.1. Block diagram of the ESP32-based multi-sensor disaster monitoring node

D. Sensor Node Design and Data Acquisition

Each sensor node is built around an ESP32 microcontroller and integrates multiple environmental sensors, including rainfall, soil moisture, ultrasonic water level, vibration, flame, and gas sensors. This combination enables the detection of a wide range of disaster events such as floods, landslides, earthquakes, fires, and gas leaks. The ESP32 serves as the central processing unit, handling sensor interfacing, data acquisition, and communication tasks.

The sensor nodes continuously sample environmental data at predefined intervals and perform preliminary threshold-based evaluation at the node level. This local processing approach helps identify abnormal conditions while minimizing unnecessary data transmission. By transmitting only relevant event-based information, the system conserves energy and reduces communication overhead, making the sensor nodes suitable for long-term deployment in remote and power-constrained environments

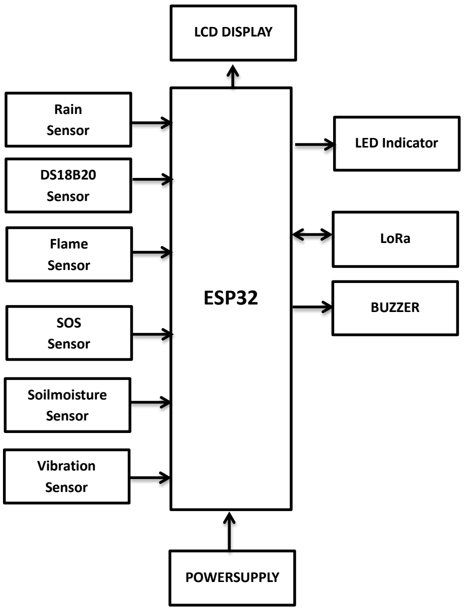


Fig. 2 shows the functional block diagram of the ESP32-based sensor node with LoRa communication and peripheral modules.

E. LoRa Communication Network

LoRa RA-02 modules are used to enable long-range wireless communication between distributed sensor nodes and the central gateway. The network is designed for low transmission power while maintaining reliable data delivery under varying environmental conditions. Using chirp spread spectrum (CSS) modulation, LoRa provides high receiver sensitivity and strong interference resistance, making it suitable for disaster-prone and infrastructure-deficient regions.

The LoRa network supports communication over several kilometres, enabling wide-area coverage with minimal gateway deployment and reduced infrastructure cost. Its low power consumption allows sensor nodes to operate for extended periods on battery power with optional solar support. Event-based data transmission is employed to reduce network congestion and energy usage while ensuring timely alert generation. Overall, LoRa communication ensures scalable, energy-efficient, and reliable data transmission for effective early-warning dissemination in remote areas.

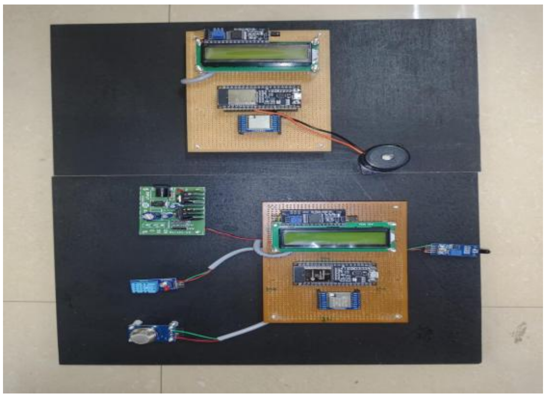


Fig. 3 illustrates the hardware prototype used for experimental validation of the proposed early-warning system.

F. Gateway and AI-Based Decision Module

The central gateway acts as the data aggregation and processing unit for the proposed system. It receives sensor data from multiple distributed nodes through the LoRa communication network and forwards the information to an embedded AI-based decision module for analysis. The gateway is designed to operate independently of internet connectivity, ensuring continuous functionality during communication outages and power failures commonly observed during disaster events.

The AI decision module analyzes multi-sensor inputs to classify the type and severity of detected disasters using predefined models and rule-based inference. By correlating data from multiple sensors, the system improves detection accuracy and reduces false alarms compared to single-parameter threshold-based approaches. Based on the analysis results, the system generates context-aware alerts and safety instructions tailored to the identified disaster scenario rather than generic warnings. These alerts are delivered locally through visual indicators, LCD displays, and audio alarms, enabling timely and effective response by affected communities even in the absence of personal communication devices or external networks.

G. Thingspeck IoT Server Intergration

To enable remote monitoring and data visualization, the proposed system integrates the ThingSpeak IoT server as an optional cloud-based data platform. The central gateway uploads selected sensor data and alert information to the ThingSpeak server when internet connectivity is available. This integration allows real-time visualization of environmental parameters such as rainfall, soil moisture, water level, vibration intensity, gas concentration, and fire detection status through graphical dashboards.

ThingSpeak provides time-stamped data storage and supports MATLAB-based analytics, which can be used for post-disaster analysis and system performance evaluation. The platform enables authorized users, such as disaster management authorities, to remotely access historical and real-time sensor data through web or mobile interfaces. This feature enhances situational awareness and supports informed decision-making during emergency response and recovery operations.

The integration of ThingSpeak does not affect the core functionality of the proposed system, as all critical alert generation and decision-making processes are performed locally at the gateway. In the absence of internet connectivity, the system continues to operate autonomously and delivers alerts through local indicators. When connectivity is restored, data synchronization with the ThingSpeak server resumes automatically. This hybrid architecture combines the reliability of local processing with the benefits of cloud-based monitoring, making the system both resilient and scalable.

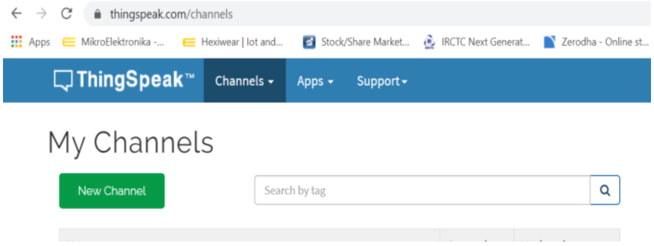


Fig. 4 ThingSpeak IoT platform showing the channel creation interface used for cloud-based data storage and visualization of sensor parameters transmitted from the disaster monitoring system.

II. SOFTWARE DESCRIPTION AND PROGRAM IMPLEMENTATION

This section describes the software architecture and program implementation of the proposed adaptive AI-driven LoRa-based early-warning system. The software framework is designed to ensure reliable sensor data acquisition, efficient communication, intelligent disaster classification, and real-time alert generation. The system software is divided into two major components: firmware for the distributed sensor nodes and application software for the central gateway.

A. Software Architecture

The overall software architecture of the proposed system follows a modular and layered design approach to improve system reliability, scalability, and ease of maintenance. Each functional module is designed independently and integrated to achieve coordinated system operation. The major software modules include sensor data acquisition, preprocessing and filtering, LoRa communication handling, AI-based decision logic, alert generation, and cloud communication.

The sensor node firmware is responsible for real-time sensor sampling, preliminary threshold evaluation, power management, and LoRa-based data transmission. The gateway software aggregates data from multiple nodes, executes the AI-based disaster classification algorithm, generates alerts, and optionally uploads data to the ThingSpeak IoT cloud platform. This modular software architecture enables efficient real-time operation while maintaining low power consumption and high reliability.

Firmware Design of Sensor Node

The sensor node firmware was developed using the Arduino IDE platform with embedded C/C++ programming. The ESP32 microcontroller serves as the central processing unit, handling multi-sensor interfacing, data acquisition, local threshold evaluation, and LoRa communication. Each sensor is interfaced through appropriate analog or digital input channels, and periodic sampling is performed at predefined time intervals.

To minimize power consumption, the firmware implements sleep modes and event-based transmission strategies. During normal environmental conditions, the microcontroller operates in low-power idle mode. When abnormal sensor readings exceed predefined thresholds, the system transitions into active mode, processes the sensor data, and transmits event-based alerts to the central gateway using LoRa communication.

Noise filtering and signal smoothing techniques are applied to reduce false triggers caused by environmental fluctuations. This approach enhances system stability and improves detection accuracy. The firmware design ensures robust operation under dynamic environmental conditions while maintaining minimal energy consumption.

Gateway Software and AI Decision Logic

The central gateway software is responsible for collecting data packets from multiple distributed sensor nodes, processing the received data, executing the AI-based disaster classification algorithm, and generating real-time alerts. The gateway firmware was also implemented using embedded C/C++ programming on the ESP32 platform.

The AI-based decision module utilizes a rule-based inference mechanism combined with adaptive threshold filtering to analyze multi-sensor inputs. By correlating sensor parameters such as rainfall, soil moisture, water level, vibration, flame detection, and gas concentration, the system accurately classifies disaster types and estimates severity levels. This multi-sensor fusion approach significantly improves detection reliability and reduces false alarm rates compared to conventional single-parameter threshold-based methods.

Upon disaster detection, the gateway triggers visual indicators, LCD display messages, and audio alarms to alert nearby populations. In addition, when internet connectivity is available, the gateway uploads sensor readings and alert data to the ThingSpeak IoT server for real-time monitoring and data visualization.

Communication Protocol and Data Format

A lightweight custom communication protocol was implemented to enable efficient data transmission between sensor nodes and the gateway. Each data packet contains a unique node identification number, timestamp, sensor readings, and event flags indicating abnormal conditions. This structured data format allows fast processing and accurate interpretation at the gateway.

LoRa communication parameters such as spreading factor, bandwidth, and coding rate were optimized to ensure reliable long-range transmission with minimal power consumption. Event-based packet transmission reduces network congestion and improves system scalability, enabling the deployment of a large number of sensor nodes over wide geographical areas.

Algorithm and Flowchart Description

The overall operational algorithm of the proposed system follows a sequential workflow comprising sensor data acquisition, preprocessing, anomaly detection, AI-based classification, and alert generation. Initially, sensor nodes continuously monitor environmental parameters and compare readings with predefined threshold values. When abnormal conditions are detected, data is transmitted to the gateway.

At the gateway, the AI-based decision module processes the incoming multi-sensor data and determines the disaster type and severity level. Based on this analysis, appropriate safety instructions and alert signals are generated. Fig. X illustrates the flowchart of the complete software operation of the proposed system.

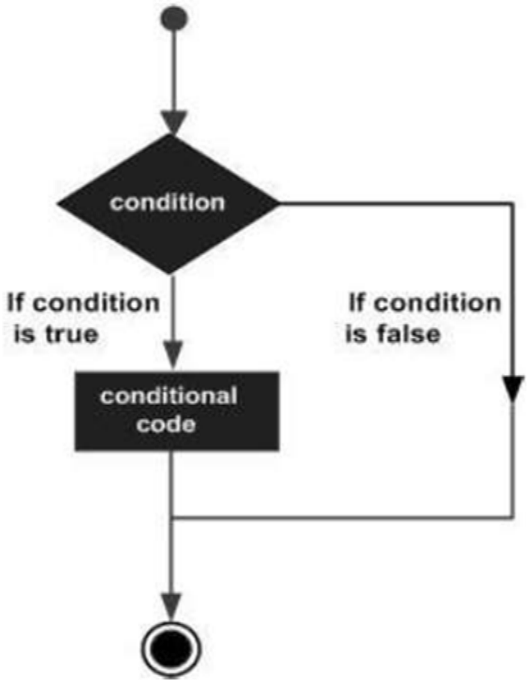


Fig.5. Flowchart of the software operation and AI-based disaster classification process

III. EXPERIMENTAL SETUP AND RESULTS

This section presents the experimental setup and performance evaluation of the proposed adaptive AI-driven LoRa-based early-warning system. The objective of the experimental study is to validate the reliability, efficiency, and effectiveness of the system under practical operating conditions. A hardware prototype consisting of ESP32-based multi-sensor nodes and a centralized LoRa gateway was implemented and tested in both controlled and simulated real-world environments. Key performance aspects such as communication range, power consumption, response time, and disaster classification accuracy were analyzed. The obtained results are discussed to demonstrate the system's capability to provide timely and reliable alerts in disaster-prone remote regions..

A. Experimental Setup

The experimental setup of the proposed Adaptive AI-driven LoRa-based Early Warning System was designed to evaluate its performance under realistic operating conditions. A hardware prototype consisting of multiple ESP32-based sensor nodes and a centralized LoRa gateway was developed and tested in both controlled laboratory environments and simulated field conditions.

Each sensor node was built using an ESP32 microcontroller interfaced with multiple environmental sensors, including a rain sensor, soil moisture sensor, ultrasonic water-level sensor, vibration sensor, flame sensor, and gas sensor. These sensors were selected to monitor critical environmental parameters associated with common natural and industrial disasters such as floods, landslides, earthquakes, fires, and gas leaks. The sensor nodes were powered using rechargeable batteries with optional solar charging support to simulate deployment in remote and off-grid regions.

LoRa RA-02 modules operating in the 433 MHz frequency band were used to establish long-range wireless communication between the distributed sensor nodes and the central gateway. The LoRa parameters such as spreading factor, bandwidth, and transmission power were configured to achieve reliable communication with low power consumption. Event-based data transmission was implemented so that sensor nodes transmit data only when abnormal conditions are detected, thereby conserving energy and reducing network congestion.

The central gateway was implemented using an ESP32 microcontroller integrated with a LoRa receiver, LCD display, buzzer, and LED indicators. The gateway hosted the embedded AI-based decision module responsible for processing multi-sensor data, classifying disaster type and severity, and generating context-aware alerts. The gateway was capable of operating independently of internet connectivity to ensure uninterrupted functionality during disasters.

To enable cloud-based monitoring, the gateway was optionally connected to the ThingSpeak IoT server whenever internet connectivity was available. Sensor data and alert status were uploaded to the cloud for real-time visualization and historical analysis. This hybrid setup allowed evaluation of both autonomous local operation and cloud-assisted monitoring.

B. Test Methodology

The system was tested under various simulated disaster scenarios to evaluate its effectiveness and reliability. Flood conditions were simulated by gradually increasing water levels near the ultrasonic sensor while rainfall intensity was emulated using the rain sensor. Landslide risk was tested by increasing soil moisture content beyond predefined thresholds and introducing vibration patterns. Fire and gas leakage scenarios were tested using controlled flame and gas exposure near the respective sensors. Earthquake-like vibrations were simulated using mechanical disturbances applied to the vibration sensor.

During each test scenario, parameters such as sensor response time, LoRa communication reliability, alert generation delay, and system stability were recorded. The power consumption of the sensor nodes was also monitored to assess suitability for long-term deployment in power-constrained environments.

C. Performance Metrics

To quantitatively evaluate the effectiveness of the proposed early-warning system, several key performance metrics were considered. These include communication range, packet delivery ratio (PDR), system latency, power consumption, and disaster classification accuracy. These parameters provide a comprehensive assessment of the system’s reliability, efficiency, and suitability for long-term deployment in remote and disaster-prone environments

Communication range was measured as the maximum distance at which reliable data transmission between sensor nodes and the gateway could be maintained without packet loss. Packet delivery ratio was calculated as the ratio of successfully received packets to the total number of transmitted packets. System latency refers to the total time delay from sensor data acquisition to alert generation at the gateway. Power consumption was measured to estimate battery lifetime under continuous monitoring conditions. Disaster classification accuracy was evaluated by comparing AI-based system predictions with known ground-truth conditions during controlled experiments.

These performance metrics collectively determine the feasibility of the proposed system for real-world disaster management applications, particularly in infrastructure-deficient regions.

D. Communication Performance Evaluation

The LoRa communication performance was evaluated by deploying sensor nodes at distances ranging from 200 meters to 5 kilometers under both semi-urban and open-field conditions. The experiments demonstrated reliable communication up to 4.5 km in open environments and approximately 2.8 km in built-up areas with obstacles. The reduction in communication range in semi-urban environments was primarily due to signal attenuation caused by buildings, vegetation, and terrain variations.

The packet delivery ratio (PDR) remained above 96% for distances up to 3 km and above 90% for distances up to 4.5 km in open-field conditions. In semi-urban environments, the PDR was observed to be above 93% up to 2 km and approximately 88% at 2.8 km. Beyond these ranges, signal degradation resulted in increased packet loss due to path loss, shadowing, and interference effects. These results confirm the suitability of LoRa technology for reliable long-range data transmission in disaster monitoring applications.

End-to-end latency, measured from sensor data acquisition to alert generation at the gateway, consistently remained below 2.5 seconds. This low response time ensures rapid dissemination of emergency alerts, which is essential for effective disaster management. Furthermore, the implementation of event-based data transmission significantly reduced network congestion and power consumption, improving system reliability during high-activity periods. Overall, the results validate the effectiveness of the proposed communication architecture for real-time early-warning systems in remote and infrastructure-deficient regions.

E. Power Consumption Analysis

Power efficiency is a critical design requirement for wireless sensor networks deployed in remote and disaster-prone regions, where access to reliable power sources is limited. The proposed system was experimentally evaluated under continuous monitoring conditions to analyze energy consumption patterns and assess long-term operational feasibility.

The ESP32-based sensor nodes consumed an average current of 70–90 mA during active sensing, processing, and data transmission phases, while the current consumption was reduced to less than 10 mA during idle monitoring and sleep states. By incorporating event-based data transmission and optimized duty cycling mechanisms, the overall power consumption of the sensor nodes was significantly minimized. This strategy ensures that sensor nodes remain in low-power states for most of the operational time and activate high-power modules only when abnormal environmental conditions are detected.

Using a 3000 mAh rechargeable lithium-ion battery, the sensor nodes achieved an operational lifetime of approximately 7–10 days under continuous monitoring conditions. With the integration of solar-assisted charging, the operational lifetime can be extended beyond 30 days, making the system suitable for long-term deployment in off-grid and remote environments. The low energy consumption of LoRa communication further contributes to prolonged battery life by enabling long-range transmission at minimal power levels.

The central gateway unit, powered using a stabilized DC supply with integrated battery backup, demonstrated stable and reliable performance with negligible power fluctuations. The gateway maintained uninterrupted operation during temporary power outages, ensuring continuous monitoring and alert generation. These experimental results confirm that the proposed system offers an energy-efficient and sustainable solution for large-scale disaster monitoring applications, significantly reducing maintenance requirements and operational costs.

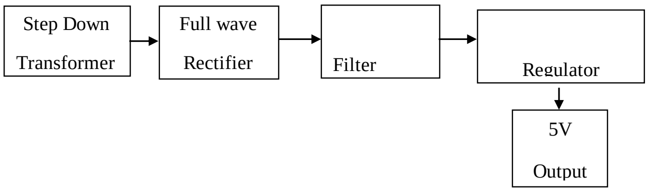


Fig. 4 Block diagram of regulated DC power supply unit

F. AI-Based Disaster Classification Accuracy

The embedded AI decision module was evaluated using datasets collected during controlled disaster simulations. A rule-based inference system combined with threshold-based filtering was employed to classify disaster types such as floods, landslides, earthquakes, fires, and gas leaks.

Experimental results demonstrated an overall classification accuracy of 94.6%, with flood detection accuracy of 96.2%, fire detection accuracy of 98.1%, gas leakage detection accuracy of 97.4%, and earthquake vibration detection accuracy of 92.5%. Landslide risk prediction achieved an accuracy of 89.8%, primarily influenced by soil composition and moisture variability.

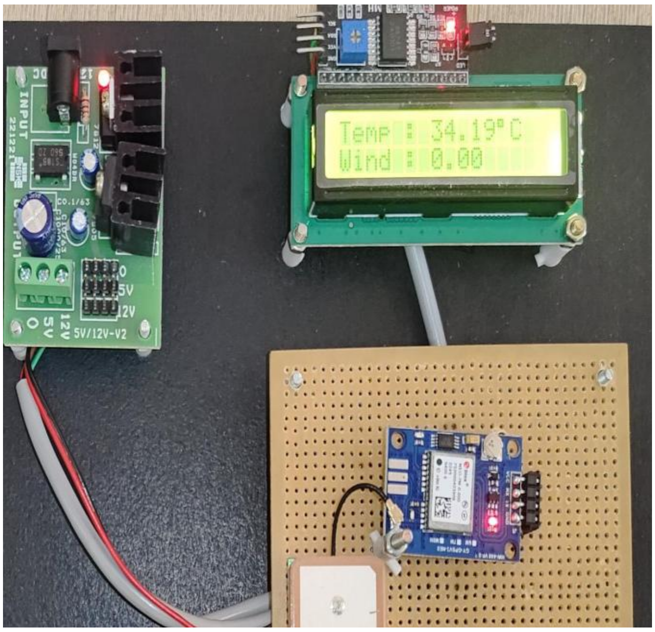
False alarm rates were significantly reduced compared to conventional single-sensor threshold-based approaches. By correlating data from multiple sensors, the system effectively differentiated between similar environmental conditions, enhancing detection reliability and minimizing unnecessary alerts.

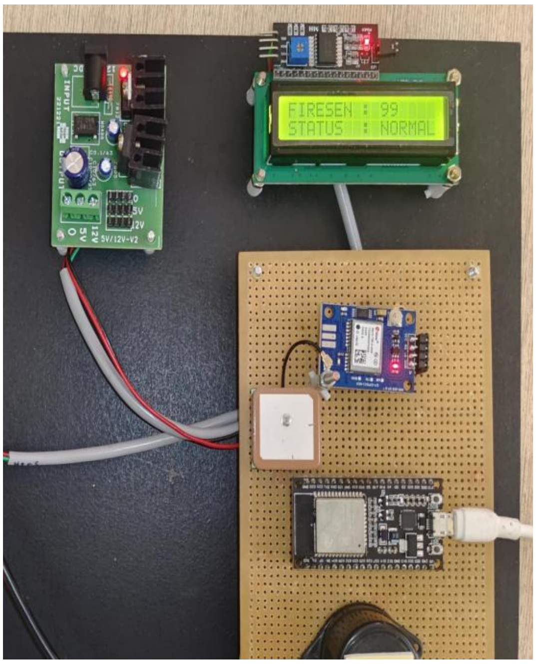
Table 1 Performance Evaluation of AI-Based Disaster Classification System

Disaster Type	**Key Sensor Inputs**	**Detection Accuracy (%)**	**False Alarm Rate (%)**
Flood	Rainfall, Water Level, Soil Moisture	96.2	2.1
Fire	Flame Sensor, Temperature	98.1	1.3
Gas Leakage	Gas Sensor Concentration	97.4	1.6
Earthquake	Vibration Sensor	92.5	3.4
Landslide	Soil Moisture, Vibration	89.8	4.2
Overall System Performance	Multi-sensor Fusion	**94.6**	**2.5**

V. DISCUSSION

Overall, the experimental results validate the effectiveness of the proposed Adaptive AI–LoRa Early-Warning System for disaster-prone remote regions. The system demonstrated reliable sensor data acquisition, stable long-range communication, rapid alert generation, and accurate disaster classification under different simulated conditions. The integration of multi-sensor fusion with embedded AI decision logic significantly reduced false alarms and improved situational awareness. Furthermore, the hybrid architecture combining autonomous local operation with optional cloud-based monitoring ensures resilience during communication failures. These results confirm that the proposed system is practical, scalable, and suitable for real-world early-warning applications.



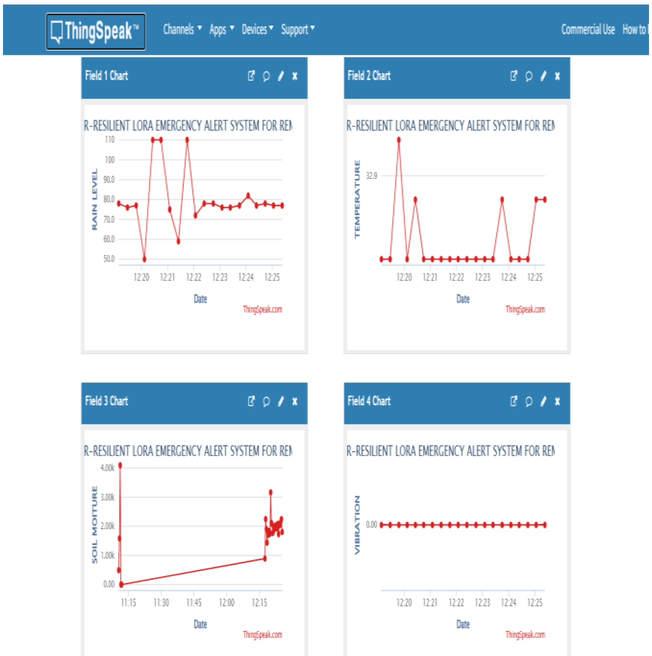


DISASTER-RESILIENT LORA EMERGENCY ALERT SYSTEM FOR RE
VILLAGES

Channel ID: 2748841

Author: mwa0000026071251

Access: Private



VI. CONCLUSION

This paper presented an adaptive AI-driven LoRa-based early-warning system for disaster monitoring in remote and disaster-prone regions. The system integrates distributed multi-sensor nodes, low-power long-range communication, and embedded AI-based decision-making to provide timely, accurate, and context-aware alerts.

Experimental results demonstrate reliable communication over several kilometers, low power consumption, rapid response time, and high disaster classification accuracy. The system operates autonomously without reliance on internet connectivity, ensuring continuous functionality during infrastructure failures.

The proposed solution offers a scalable, energy-efficient, and intelligent platform for early disaster detection and response, significantly enhancing community preparedness and resilience in vulnerable regions.

VII. ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to the Department of Electronics and Communication Engineering and the management of the institution for providing the necessary infrastructure, laboratory facilities, and technical resources required to carry out this research work. The authors are also thankful to the faculty members and technical staff for their continuous guidance, encouragement, and valuable suggestions throughout the development and testing of the proposed system. Special thanks are extended to friends and peers for their cooperation and constructive feedback during experimentation and system validation.

REFERENCES

1. S. Ramesh and K. Priya, "LoRa-Based Flood Monitoring and Early Warning System," International Journal of Engineering Research & Technology (IJERT), vol. 8, no. 6, pp. 112–116, Jun. 2019.
2. M. Chen and Y. Wang, "Wireless Sensor Network for Landslide Detection Using Soil Moisture Sensors," IEEE Sensors Journal, vol. 20, no. 14, pp. 7854–7862, Jul. 2020.
3. A. Kumar and R. Singh, "Design of an IoT-Based Disaster Monitoring System Using LoRa Technology," in Proc. International Conference on Smart Systems and Inventive Technology (ICSSIT), IEEE, 2021, pp. 456–461.
4. J. López and D. Martinez, "Low-Power Earthquake Detection System Using Vibration Sensors and LoRaWAN," IEEE Internet of Things Journal, vol. 9, no. 5, pp. 3812–3820, Mar. 2022.
5. N. Patel and S. Verma, "AI-Assisted Emergency Alert System for Natural Disaster Management," International Journal of Advanced Computer Science and Applications (IJACSA), vol. 14, no. 2, pp. 210–217, 2023.

6. T. Nguyen and P. Tran, “Smart Village Disaster Warning System Using Solar-Powered LoRa Sensor Nodes,” IEEE Access, vol. 12, pp. 65421–65430, 2024.
7. F. Adelantado, X. Vilajosana, P. Tuset-Peiró, B. Martinez, J. Melia-Segui, and T. Watteyne, “Understanding the Limits of LoRaWAN,” IEEE Communications Magazine, vol. 55, no. 9, pp. 34–40, Sept. 2017.
8. K. Mekki, E. Bajic, F. Chaxel, and F. Meyer, “A Comparative Study of LPWAN Technologies for Large-Scale IoT Deployment,” ICT Express, vol. 5, no. 1, pp. 1–7, Mar. 2019.
9. A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, “Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications,” IEEE Communications Surveys & Tutorials, vol. 17, no. 4, pp. 2347–2376, 2015.
10. OpenAI, “Large Language Models for Real-Time Decision Support and Intelligent Systems,” OpenAI Technical Report, 2023.
11. A. Augustin, J. Yi, T. Clausen, and W. Townsley, “A study of LoRa: Long range and low power networks for the Internet of Things,” Sensors, vol. 16, no. 9, pp. 1–18, 2016.
12. R. Sanchez-Iborra and M. Cano, “State of the art in LP-WAN solutions for industrial IoT services,” Sensors, vol. 16, no. 5, pp. 1–14, 2016.
13. M. Mohanty, S. K. Jena, and S. Patnaik, “IoT based disaster monitoring and early warning system,” International Journal of Engineering Research & Technology, vol. 8, no. 6, pp. 120–125, 2019.
14. S. Madakam, R. Ramaswamy, and S. Tripathi, “Internet of Things (IoT): A literature review,” Journal of Computer and Communications, vol. 3, no. 5, pp. 164–173, 2015.
15. L. Da Xu, W. He, and S. Li, “Internet of Things in industries: A survey,” IEEE Transactions on Industrial Informatics, vol. 10, no. 4, pp. 2233–2243, Nov. 2014.
16. M. Centenaro, L. Vangelista, A. Zanella, and M. Zorzi, “Long-range communications in unlicensed bands: The rising stars in the IoT and smart city scenarios,” IEEE Wireless Communications, vol. 23, no. 5, pp. 60–67, Oct. 2016.
17. J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, “Internet of Things (IoT): A vision, architectural elements, and future directions,” Future Generation Computer Systems, vol. 29, no. 7, pp. 1645–1660, 2013.
18. S. Sendra, J. Lloret, M. Garcia, and J. Toledo, “Power saving and energy optimization techniques for wireless sensor networks,” Journal of Communications, vol. 6, no. 6, pp. 439–459, 2011.
19. C.Nagarajan and M.Madheswaran - ‘Stability Analysis of Series Parallel Resonant Converter with Fuzzy Logic Controller Using State Space Techniques’- Taylor &Francis, Electric Power Components and Systems, Vol.39 (8), pp.780-793, May 2011. DOI: 10.1080/15325008.2010.541746
20. C.Nagarajan and M.Madheswaran - ‘Experimental verification and stability state space analysis of CLL-T Series Parallel Resonant Converter’ - Journal of Electrical Engineering, Vol.63 (6), pp.365-372, Dec.2012. DOI: 10.2478/v10187-012-0054-2
21. C.Nagarajan and M.Madheswaran - ‘Performance Analysis of LCL-T Resonant Converter with Fuzzy/PID Using State Space Analysis’- Springer, Electrical Engineering, Vol.93 (3), pp.167-178, September 2011. DOI 10.1007/s00202-011-0203-9
22. S.Tamilselvi, R.Prakash, C.Nagarajan,“Solar System Integrated Smart Grid Utilizing Hybrid Coot-Genetic Algorithm Optimized ANN Controller” Iranian Journal Of Science And Technology-Transactions Of Electrical Engineering, DOI10.1007/s40998-025-00917-z,2025
23. S.Tamilselvi, R.Prakash, C.Nagarajan,“ Adaptive sliding mode control of multilevel grid-connected inverters using reinforcement learning for enhanced LVRT performance” Electric Power Systems Research 253 (2026) 112428, doi.org/10.1016/j.epsr.2025.112428
24. S.Thirunavukkarasu, C. Nagarajan, 2024, “Performance Investigation on OCF and SCF study in BLDC machine using FTANN Controller," Journal of Electrical Engineering And Technology, Volume 20, pages 2675–2688, (2025), doi.org/10.1007/s42835-024-02126-w
25. Nagarajan, M.Madheswaran and D.Ramasubramanian- ‘Development of DSP based Robust Control Method for General Resonant Converter Topologies using Transfer Function Model’- Acta Electrotechnica et Informatica Journal , Vol.13 (2), pp.18-31,April-June.2013, DOI: 10.2478/aeei-2013-0025.
26. C.Nagarajan and M.Madheswaran - ‘DSP Based Fuzzy Controller for Series Parallel Resonant converter’- Springer, Frontiers of Electrical and Electronic Engineering, Vol. 7(4), pp. 438-446, Dec.12. DOI 10.1007/s11460-012-0212-0.
27. C.Nagarajan and M.Madheswaran - ‘Experimental Study and steady state stability analysis of CLL-T Series Parallel Resonant Converter with Fuzzy controller using State Space Analysis’- Iranian Journal of Electrical & Electronic Engineering, Vol.8 (3), pp.259-267, September 2012.

28. C.Nagarajan and M.Madheswaran, “Analysis and Simulation of LCL Series Resonant Full Bridge Converter Using PWM Technique with Load Independent Operation” has been presented in ICTES’08, a IEEE / IET International Conference organized by M.G.R.University, Chennai.Vol.no.1, pp.190-195, Dec.2007
29. Suganthi Mullainathan, Ramesh Natarajan, “An SPSS and CNN modelling based quality assessment using ceramic materials and membrane filtration techniques”, Revista Materia (Rio J.) Vol. 30, 2025, DOI: https://doi.org/10.1590/1517-7076-RMAT-2024-0721
30. M Suganthi, N Ramesh, “Treatment of water using natural zeolite as membrane filter”, Journal of Environmental Protection and Ecology, Volume 23, Issue 2, pp: 520-530,2022
31. A. Lavric and V. Popa, “Internet of Things and LoRa™ low-power wide-area networks: A survey,” Electronics, vol. 8, no. 5, pp. 1–27, 2019.
32. N. Sornin, M. Luis, T. Eirich, T. Kramp, and O. Hersent, LoRaWAN Specification, LoRa Alliance, 2015.
33. Mathew, A. Cybersecurity 5.0: From Firewalls to Fully Autonomous Digital Protection.
34. Rengarajan, A. (2025). Cloud-Based AI-Driven Threat Detection Framework for Smart Grid Cybersecurity. International Journal of Future Innovative Science and Technology (IJFIST), 8(6), 16065.
35. Anbazhagan, K. (2025). Next-Generation Enterprise Cloud AI for Healthcare: Secure CNN Pipelines and Privacy Controls. International Journal of Future Innovative Science and Technology (IJFIST), 8(6), 15980.
36. Socrates, S., Shanmugapriya, M., Murugeshwari, B., & Angalaeswari, S. (2024). Efficient Design for Implantable Device Constant Current Induction Doubly Fed Generating Incorporating Grid Connectivity. In Intelligent Solutions for Sustainable Power Grids (pp. 382-392). IGI Global Scientific Publishing.
37. Sugumar, R. (2026). Performance Optimization Frameworks for Financial Web Platforms with Real-Time Transaction Processing. International Journal of Engineering & Extended Technologies Research (IJEETR), 8(2), 600-611.
38. Anbazhagan, K. (2025). AI Driven Zero Trust Security Model for Enterprise Data Protection and Intelligent Infrastructure Management. International Journal of Technology, Management and Humanities, 11(03), 101-107.
39. Prabha, P. S., & Rengarajan, A. (2025). ENHANCING CLOUD RESOURCE ALLOCATION WITH VISION TRANSFORMER, DEEP REINFORCEMENT LEARNING, AND IMPROVED SHRIKE OPTIMIZATION ALGORITHM. Corrosion Management ISSN: 1355-5243, 35(2), 233-245.
40. Vimal, V. R., & Banerjee, J. S. (2025). Integrating PSO, GA, and ACO for Optimized ECG Feature Selection and Classification of Cardiac Disorders. SGS-Engineering & Sciences, 1(5).
41. Gopinathan, V. R. (2023). Cloud-First AI Security Architecture for Protecting Enterprise Digital Ecosystems and Financial Networks. International Journal of Research and Applied Innovations, 6(6), 10031-10039.
42. Mathew, A. A Secure, Trustworthy, and Regulated Framework for AI Agents in Distributed Networks.
43. Anbazhagan, K. (2025). Secure AI Enabled Enterprise Ecosystems for Fraud Prevention Compliance Automation and Real Time Analytics. International Journal of Multidisciplinary Research in Science, Engineering, Technology & Management, 1(4), 6-13.
44. Soundappan, S. J. (2026). Building Trustworthy AI: Explainability and Security in Modern Cloud-Native Data-Driven Ecosystem Platforms. International Journal of Engineering & Extended Technologies Research (IJEETR), 8(2), 570-579.
45. Sugumar, R. (2025). Cyber-Secure Cloud Architecture Integrating Network and API Controls for Risk-Aware SAP Healthcare Data Platforms. International Journal of Humanities and Information Technology, 7(4), 53-60.
46. Vimal, V. R., & Banerjee, J. S. (2025). Integrating PSO, GA, and ACO for Optimized ECG Feature Selection and Classification of Cardiac Disorders. SGS-Engineering & Sciences, 1(5).
47. Gopinathan, V. R. (2025). AI-Powered Kubernetes Orchestration for Complex Cloud-Native Workloads. International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), 8(6), 13215-13225.
48. Mathew, A. From Conversation to Command Execution: A Comparative Threat Modeling and Risk Analysis of OpenClaw and ChatGPT. Risk, 100(1).
49. Inbavalli, M., & Arasu, T. (2015). Efficient Analysis of Frequent Item Set Association Rule Mining Methods. International Journal of Scientific & Engineering Research, 6(4).
50. Sugumar, R. (2025). Secure and Explainable AI Systems in Cloud-Based Applications: Bridging Trust and Performance. International Journal of Engineering & Extended Technologies Research (IJEETR), 7(4), 10328-10335.
51. Rajasekar, M. (2025). Risk-Aware Generative AI and Machine Learning Frameworks for Privacy-Preserving Banking and Trade Analytics over Cloud and 5G Networks. International Journal of Computer Technology and Electronics Communication, 8(4), 11078-11086.

52. Gopalakrishnan, S., Dhinakaran, D., Raja, S. E., Raghavan, P., & Girija, M. S. (2026). Fusion-Driven Medical Image Encryption Framework with Entropy-Calibrated Control and Integrity Assurance. KSII Transactions on Internet & Information Systems, 20(2).
53. G. Vimal Raja, K. K. Sharma (2014). Analysis and Processing of Climatic data using data mining techniques. Envirogeochimica Acta 1 (8):460-467.