Ecogeoguard: A Dual Approach to Environmental Safety and Crop Yield

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Abstract. A community-focused AI-IoT technology, EcoGeoGuard combines livestock safety tracking, precision agriculture analytics, and multi-sensor geophysical monitoring into a single real-time intelligence ecosystem. In addition to GPS-enabled livestock trackers, the system uses inexpensive environmental sensors, such as MEMS accelerometers, geophones, tilt sensors, soil-moisture probes, and BME280 weather modules, all connected via a hybrid LoRa/NB-IoT/Wi-Fi communication architecture. Before being fed into a cloud-based analytics pipeline via AWS IoT Core, data is processed at the edge using FFT-based vibration analysis and threshold filtering. Machine learning algorithms, such as Random Forests, Gradient Boosting, Linear Regression, and K-Means clustering, are used to analyse time-series streams to identify early warning signs of slope instability, optimise the use of irrigation and fertilisers, and detect cow movements outside designated safety zones. The anomaly management layer calculates risk ratings and activates multi-channel alerts via dashboards, SMS, mobile applications, and local siren units. EcoGeoGuard is a holistic early-warning and decision-support platform to safeguard livestock and population in disaster-prone regions, enhance productive rural agriculture, and enhance climate resilience. It includes network resilience and energy-efficient, solar-powered nodes.

Keywords: Landslide prediction; smart agriculture; livestock tracking; disaster management; climate resilience; early warning systems; artificial intelligence; rural sustainability

1. INTRODUCTION

Rapidly shifting climate patterns, unstable slopes, erratic rainfall, and environmental degradation continue to be problems for India's rural and mountainous areas [9, 12] in Fig.1. Unpredictable weather impacts agricultural output and disturbs local livelihoods, while landslides and soil erosion still pose a hazard to human settlements, farmlands, and cattle [2, 17]. Conventional techniques for tracking geological dangers, farm conditions, and cattle movements often function independently and provide scant and dispersed situational data [24]. An integrated, real-time approach is required to address these interconnected challenges holistically because

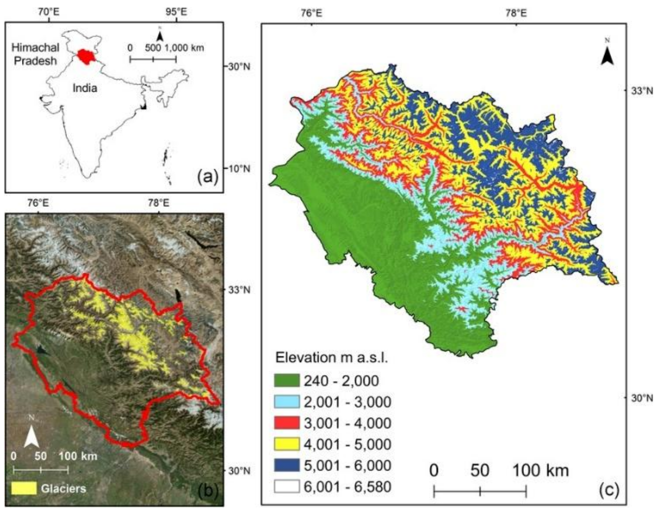

Fig.1. Landslide Prone Area (Source- Google Maps or QGIS) agriculture and animal husbandry are the main sources of income for populations in susceptible areas [12]. Being offered as an adaptive platform with the concept of geofenced livestock trackers and an intelligent agronomical advisor integrated with the feature of a multi-sensor environmental sensor, EcoGeoGuard becomes a full-fledged AI-IoT system that will result in the improved resilience of rural areas [13, 25]. This system records the vibration, slope deformation, soil saturation, and atmospheric changes that are the main signs of the presence of a landslip and flood risk, which are captured by the MEMS-based accelerators, geophones, tilt sensors, soil-moisture sensors, and weather sensors [1, 3, 7]. Also, EcoGeoGuard includes livestock collars featuring GPS and LoRa solutions to track the movement of animals in real time, identify hazardous locations, and issue early warnings during an emergency [24]. The platform is designed with AWS IoT Core, time-series storage, and an anomaly and fault management layer, enabling the quick delivery of risk scores, warnings, and farming advice via dashboards, mobile alerts, SMS, and local sirens. EcoGeoGuard helps to adapt to climate changes, enhance the safety of rural populations and pursue sustainable development objectives across the sensitive Indian land by integrating livestock protection, smart farming, and disaster forecasting into one intelligent system [12, 29].

Motivation: Because of rapid, constant environmental changes, people living in mountain areas like Himachal Pradesh are affected. All previous studies focused more on either detecting it first or addressing the damage it causes afterwards, but not on an integrated approach that alerts people through common channels about the hazard and takes the necessary steps accordingly. Also, showing concern about wildlife and agriculture, as they are important too. The idea of EcoGeoGuard is motivated by these aspects of improving the condition of people and wildlife existing in those areas using AI- IoT technology.

2. LITERATURE REVIEW

Many recent research studies in landslide monitoring and forecasting demonstrate how sensor technology can detect landslides before they occur. Sensor-based technologies have been utilised to detect ground vibrations early on, which can help identify unstable slopes. One example of this type of sensor technology is a highly sensitive MEMS accelerometer developed by Najafabadi et al., which can detect early ground vibrations caused by the instability of a slope [1]. In another study, Binali et al. reviewed and discussed low-cost MEMS accelerometers that can be used for monitoring slope vibrations and emphasised their advantages in terms of low power consumption, cost effectiveness and ease of use [8]. In addition, Setiawan, Cysela and Dikshit et al. used MEMS-based inclinometers to monitor the deformation of slopes in mountainous areas and allow real-time detection of landslide risk [11], [7]. Other critical variables impacting the prediction of landslides are environmental conditions. Wicki et al. have shown that the moisture content of soil is a good indicator of slope stability; therefore, soil moisture can be used to create regional early-warning systems for landslides [3]. In addition, Sharma and Gautam have developed a soil moisture measurement system using IoT technologies to support precision irrigation and provide valuable data that can be used to support environmental monitoring [19]. These examples illustrate that when attempting to develop an accurate method of predicting landslide hazards, both the geotechnical and environmental aspects must be integrated to achieve the desired results.

Improvements in IoT communication architecture have allowed for better capacity for real-time monitoring to occur. Badru et al. created a landslide early warning system based on IoT technology for implementation in hilly regions [2], while Mittal et al. considered the challenges regarding deploying sensor networks for hazard monitoring [4]. Patel et al. suggested a cloud-based IoT architecture using MQTT for reliable data transmission [27], and Yuan et al. proposed an edge-cloud collaborative framework for real-time hazard monitoring [18].

Long-range communication technologies such as LoRa and NB-IoT have also been positively impacting environmental monitoring through extensive use. Pradhan et al. developed a wireless sensor network that uses LoRa for remote environmental data gathering [16]. Alam and Hussain suggested the use of a hybrid LoRa-NB-IoT architecture to enhance connectivity for rural IoT systems [22].

In the area of landslide prediction, improvements have been achieved by using machine learning techniques, which benefit from their ability to predict landslides more accurately than threshold-based methods. For example, by using machine learning models such as decision trees and artificial neural networks to build predictive models of rainfall and environmental parameters, Pathak et al. found these models' predictive performances were far superior to those of traditional threshold-based models [17]. Li et al. also demonstrated the potential of using machine learning models to predict climate based on atmospheric parameters [20].

In addition, many recent studies highlight the need for multi-sensor data fusion and integrated monitoring systems. For example, through the combination of GNSS and accelerometer data, Jing et al. were able to achieve greater accuracy in monitoring deformation than either data source alone [14]. Similarly, Carpentieri and O'Neill reported on the success of integrating MEMS sensors with inclinometers into a system of monitoring land deformation [26]. Lastly, Rana et al. have shown that geophone-based vibration sensors can provide important support for early warning systems in response to landslides [23]. Many existing research solutions continue to focus on a single-parameter methodology for environmental sensing or isolated sensor systems. This issue demonstrates a clear need for an AI-IOT (Artificial Intelligence-Internet of Things) framework that will provide complete environmental monitoring along with early warning capabilities through sensor integration between smart agriculture, environmental sensing, and livestock.

3. METHODOLOGY

The EcoGeoGuard Framework is designed with a structured method to collect multi-sensor data through IoT devices and process that data (EDGE) through cloud-based ML Analytics and disseminate notifications through multiple channels. It is anticipated that this approach will allow for the continued monitoring of environmental monitoring, agriculture and livestock in rural, hilly areas that have an unstable surface and inconsistent weather, leading to the need for proactive support for decisions. [12, 18].
An overview of the overall method is broken down into six distinct stages: sensor placement and measurement, preprocessing feature extraction from the raw data, building machine learning algorithms, designing a cloud/data management infrastructure to handle all the data processed by the machine learning algorithms, sending out notifications and/or visualising alerts, and finally, assessing the accuracy and consistency of the machine learning results. EcoGeoGuard employs a structured approach to problem solving, which consists of 4 steps: sensing, preprocessing, ML analysis, and alert generation.

1. Sensor Deployment and Data Acquisition
The proposed solution involves the use of sensors in three distinct locations: landslide-prone areas, agricultural fields and pastures [16, 22]. Each of the different types of sensors, as mentioned in Table 1, will make it possible to collect complete data on different geologic, environmental and agricultural measurements using relatively inexpensive and adaptable types of sensors. As per Table 1

Table 1. Sensors and Data Acquisition

Domain	Sensor / Device	Measured Parameters	Purpose
Geological Monitoring	MEMS Accelerometer (MPU6050)	3-axis acceleration, RMS vibration, FFT frequency-band energy	Detection of micro-tremors and vibration patterns related to slope instability
Geological Monitoring	Geophone	Low-frequency ground vibration, STA/LTA ratio	Identification of seismic anomalies and early landslide signatures
Geological Monitoring	Tilt / Inclinometer Sensor	Tilt angle, slope deformation, drift trend	Monitoring gradual slope movement
Geological Monitoring	Soil Moisture Sensor	Soil saturation, moisture fluctuation	Assessment of slope stability and irrigation needs
Environmental Monitoring	BME280 Weather Sensor	Temperature, humidity, barometric pressure	Detection of rainfall and extreme weather trends
Livestock Monitoring	GPS Module (LoRa/GPS collar)	Latitude, longitude, movement patterns	Real-time livestock tracking and geofencing
Livestock Monitoring	RFID Tag (optional)	Animal identification	Livestock identity verification

2. Data Preprocessing and Feature Extraction
Methodical preprocessing will be performed on the acquired data to produce reliable results from machine learning. The following sections will outline how preprocessing is achieved; each subset of data will be processed through the following methods:

- Noise Reduction

Sensor data is contaminated by noise sources; noise originating from sources such as wind, rain, and ground motion must be removed from sensor data before inputting it into machine learning algorithms. Other sources of noise can come from miscalibration or malfunctioning sensors. Filter techniques are utilised [5], [23], including moving average filters and FFT-based frequency analysis, to remove any unwanted or unneeded signal components

- Feature Engineering

The features that will be extracted include:
RMS vibration strength, FFT frequency band strength, STA/LTA ratio (seismic), Tilt (drift slope), Pressure drops (trend), Humidity (trend), Soil moisture (change rate)
The data obtained from each feature provides a multi-dimensional data space available for input into machine learning.

- Normalization

All sensor inputs (vibration, moisture, tilt and weather) will be normalised and scaled in such a way that each input has equal weight when being used as input to machine learning algorithms.

3. Machine Learning Model Development
EcoGeoGuard uses machine learning algorithms to predict landslides, analyse smart agriculture and protect livestock with both supervised and unsupervised machine learning models.

- Landslide Prediction Module

The Landslide Prediction Module uses soil moisture saturation, STA- LTA Seismic Ratios, RMS Vibration Energy, the Power of Frequency Bands in Fast Fourier Transforms (FFTs), the Drift Characteristics of Tiling over time (Drift News), and the Pressure Drop Rate. Columns [3], [6], and [23] calculate Landslide Risk Probability Scores on a scale of 0-1. An alert is generated when the probability score is greater than the predefined warning limit.

- Smart Agriculture Analysis Module

The Smart Agriculture Analysis Module uses soil moisture, temperature, humidity and atmospheric conditions

- Livestock Tracking, Geofencing

The Livestock Tracking, Geofencing Module calculates real-time GPS location and time series movement of livestock.

4. Alert Generation and Visualisation
The Alert Generation and Visualisation functionality uses mobile apps, SMS, web interfaces, and audible sirens/buzzers to alert users of unusual environmental patterns and provide high-risk scores.
A centralised dashboard displays seismic events, soil moisture patterns, weather changes, animal locations, and risk levels for farmers and authorities [12].

4. EXPERIMENTAL SETUP

The multi-stage validation process of the EcoGeoGuard framework included simulation-based prototypes, physical hardware deployments, and the generation of datasets for machine learning evaluation and real-time mobile app integration.
A. Prototype Validation via Simulation-Based Methods
The original prototype was designed with Proteus 8 Professional, shown in Fig.2, to ensure that all the

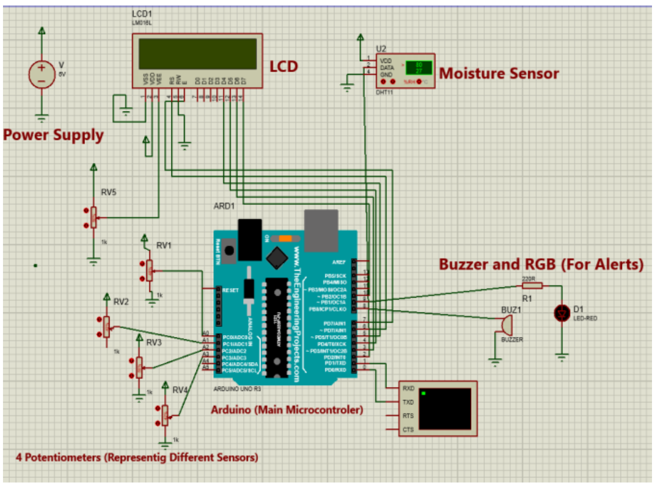

Fig.2. Simulation-Based Prototype

Functionality required by the produced hardware prior to its physical installation had been developed and reduced the risk of being deployed incorrectly [18, 22]. The main processor was an Arduino Uno (ATmega328P) [1, 9]. The varying soil moisture was used to represent increasing saturation [3], and simulating tilt would be the same as demonstrating slope [7, 11]. Simulating vibrations, for example, would be the same as stimulating micro-seismic disturbances [1, 23] and simulating atmospheric conditions was accomplished through using a DHT11 module [6, 10].

B. Physical Hardware Deployment and Data Set Creation

Once the simulations were verified as accurate, the system was constructed using actual sensors like soil moisture probes, MEMS accelerometers, geophones, tilt sensors, environmental modules, and GPS integration [1, 3, 7, 23, 24]. Data were sampled from these sensors through Arduino's 10-bit ADC (0-1023 Resolution). Data was recorded at multiple controlled conditions to analyse stable and risk scenarios. Using multiple sensor fusion parameters, including soil moisture, tilt drift, vibration energy, and atmospheric trends [14, 26]. Each associated parameter or record was classified as either "Normal" or "Risk" based on how many other associated parameters were normal or at risk.

C. Machine Learning Evaluation

The data was prepared for use through filter methods and normalisation methods [5, 23]. The derived features, such as the Vibration RMS Amplitude and the soil moisture rate, were extracted to improve Classifier Capabilities. Also, a 70:30 Train/Test Split with Cross Validation was used, and the Models used were Threshold Based Logic [4], Linear Regression, Random Forest, and Gradient Boosting, Ensemble methods; were Selected Because of their success in Environmental Prediction [9, 17]. Evaluating the performance of these models utilised metrics of accuracy, Precision, recall, and the F1 Score, and allowed comparisons with Previous Landslide Detection Systems [3, 7, 23]. As shown

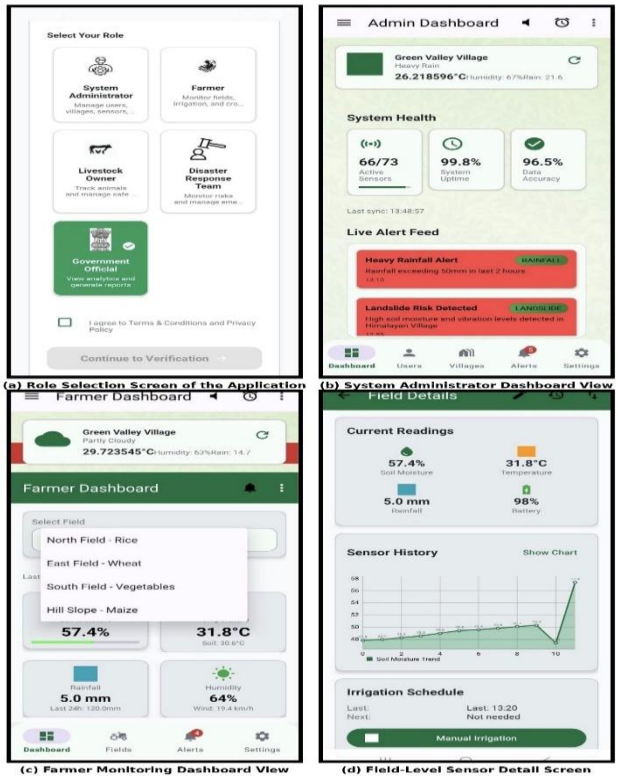

Fig. 3. Application Interface

D. Communication Architecture and Backend Integration

The developed model was incorporated into a backend framework based on edge-cloud IoT architectural standards [18]. Sensor data was converted to structured data packets and communicated using APIs compatible with LoRa–NB-IoT rural communications [16, 22, 27]. This provided a robust foundation for reliably exchanging data between hardware nodes/modules and the application programming environment.

E. Mobile Application Deployment and Alert Visualisation

The completion of the full cycle was made possible by integrating EcoGeoGuard into a specially created Android mobile app that allows for real-time environmental monitoring as well as alert visualisation. The mobile app features secure multi-role authentication along with role-based access control in accordance with the requirements for IoT-based hazard management systems [18, 27]. The dashboard presents all live sensor values, risk trend charts, and alert notifications. During the validations phase, machine-learning risk scores were displayed in real-time on the mobile application, while alert notifications were sent within 1-2 seconds of detection of critical multi-parameter criteria; thereby satisfying the requirements for immediate warning times [2, 18]. (Fig.3. demonstrate the login interface, admin dashboard, risk analytics view, as well as the live alert feed of the EcoGeoGuard mobile app.)

5. RESULTS AND DISCUSSION

A. Quantitative Sensor Evaluation

The EcoGeoGuard system was analysed in multiple parameters in controlled environments that included manipulating the environmental sensors within their respective normal and critical ranges. The sensor readings using the Arduino Uno 10-bit ADC (0-1023) were converted to the standard range of 0-5 volts and, therefore, provided the base reference for normalising the sensor readings [1, 12].

The soil moisture ranges for the electronic devices were set to provide simulated SM between 200 and 900 ADC. When the simulated readings were between 200 and 500, the soil condition would be classified as dry to normal. When the readings were greater than 700, they indicated potential saturation and slope stability issues [3, 17]. The tilt was also simulated between 300 and 800 ADC. A tilt reading below 500 indicates the slope is relatively stable. Likewise, tilt readings above 600 represent an advancing slope deformation [7, 11, 21]. The vibration/geophone outputs were measured between 250 and 900 ADC. An output reading below 400 indicates more background noise than a significant disturbance, while an output reading above 600 would be an abnormal micro-seismic disturbance [1, 8, 23].

The values for temperature 22–38°C and relative humidity 45-85% represent the minimum/maximum operational ranges for the environmental sensors attached to the EcoGeoGuard system. While atmospheric changes alone did not produce alert data, extended time periods of relative humidity above 80% create conditions leading to increased soil saturation and instability [6, 20].

An alert will only be generated when multiple environmental parameters exceed a critical threshold, as shown in Table 2, and at least 2 sensors are activated simultaneously. These multiple sensors triggering to generate alerts will dramatically reduce false-positive alerts that occur only with the activation of a single parameter threshold [4, 26].

Table 2. Normal And Critical Ranges of Simulated Sensors

Parameter	**Normal Range**	**Critical Threshold**
Soil Moisture	200–500	>700
Tilt Angle	300–500	>600
Vibration	250–400	>600
Humidity	45–70 %	>80 %

B. Machine Learning Performance

We compared the performance of supervised machine learning models developed using data collected from actual deployments to that of the traditional threshold logic systems. The following is shown in Table 3: a summary of the performance metrics included in this comparison. Gradient Boosting achieved a maximum accuracy of 93.7%, which is a spectacular improvement of 15.3% with the threshold logic model. In addition, these results support previous research, which also concluded that ensemble learning is superior to traditional methods when predicting landslides caused by rainfall [17], as well as when using AI for monitoring the environment [9, 13].

Table 3. Performance Metrics

Model	Accuracy	Precision	Recall	F1-score
Threshold Logic	78.4	75.2	72.8	73.9
Linear Regression	81.6	79.4	80.2	79.8
Random Forest	91.3	90.1	92.5	91.2
Gradient Boosting	93.7	92.8	94.2	93.5

C. Comparative Analysis with Prior Work

To validate performance improvements, EcoGeoGuard was compared with past systems shown in Fig.4. The EcoGeoGuard detectors improve upon: Soil Moisture Only: 21.7% improvement, Tilt Based: 18.7% improvement, Seismic Only: 10.7% improvement, Rainfall Based ML Methods: 5.7% improvement.

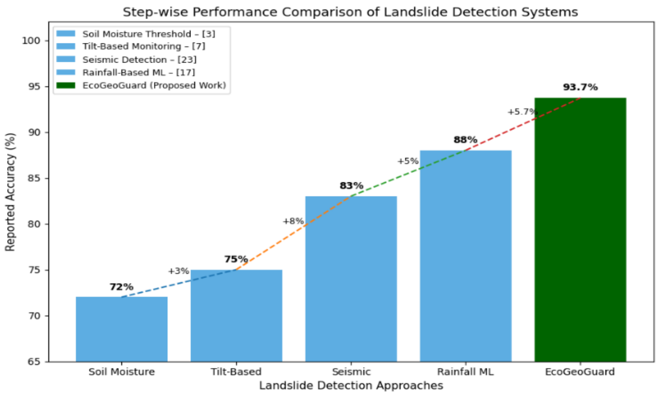

Fig. 4. Stepwise performance comparison of EcoGeoGuard with existing landslide detection systems [3, 7, 17, 23], showing superior accuracy (93.7%)

D. Alerting, System Reliability, and Mobile Validation

When multi-parameter critical conditions were detected, the system transitioned to Alert Mode from Monitoring Mode within 1–2 seconds [12, 18]. LED and buzzer alerts were activated locally, and structured sensor packets were transmitted to the back end without loss of data or buffer overflow throughout extended operations [16, 22]. The Mobile Application displays Real-time Alerts, Environmental Dashboards and Risk Trend Analytics. This confirms that the entire end-to-end pipeline from the sensor acquisition process through mobile-based decision support is operationally intact. Unlike previous systems that stopped at threshold detection [3, 7], EcoGeoGuard provides end-to-end predictive analytics with integration of user-level visualisation, facilitating enhanced field-level responsiveness in rural areas.

6. CONCLUSION AND FUTURE WORK

EcoGeoGuard has developed an AI-IOT integrated system aimed at environmental monitoring (using sensors), smart agriculture, and geo-guarding of livestock, which is designed to provide a comprehensive solution for rural and hilly regions [12, 13]. The system integrates data from vibration sensors, geophones, tilt sensors, soil moisture sensors, weather sensors, GPS collars, etc., to provide real-time analytics and alerts, allowing for better informed decision-making [1, 3, 7, 24]. Multi-sensor Fusion and machine learning algorithms such as Random Forest, Gradient Boosting, Linear Regression, and K-Means clustering improve landslide prediction accuracy and facilitate the design of intelligent irrigation systems, fertiliser predictions, and geo-fencing of livestock [6, 9, 17, 28]. Edge cloud computing and LoRa - NB - IoT communications provide the flexibility and efficiency needed to implement this system in poorly - connected areas [16, 18, 22].

Ultimately, EcoGeoGuard demonstrates the promise of an integrated system to decrease the risk of environmental hazards, increase the use of agricultural resources, and improve the safety of populations and livestock, improving climate resilience and supporting rural sustainable development [25], [29].

Future Work

The EcoGeoGuard's future development revolves around enhancing its effectiveness and precision. To this end, advancements will comprise, amongst other advances,
1. Integrating drone and satellite photographs into an extensive evaluation [15].
2. Applying reinforcement learning techniques to adaptively predict outcomes [29].
3. Using digital twins for modern geographical risk modelling [17].

Further improvements to EcoGeoGuard may include employing blockchain technology to ensure data integrity [27], developing methods to recognise various types of risks such as flooding and wildfires [13] and offering AI-aided livestock health monitoring systems [24], and providing end-users with access to result information in different languages via offline, mobile applications designed for rural geographic areas [12].

CONFLICT OF INTEREST

The authors declare no conflicts of interest regarding the current research.

AUTHOR CONTRIBUTION

First author: hardware implementation and supervision
Second author: research analysis and methodology
Third author: verified the analytical methods
Fourth author: supervisor
Fifth author: proposed the research problem
Sixth author: data collection, ML implementation
Seventh author: mobile application development and feature implementation

REFERENCES

[1] H. R. Najafabadi, A. Jafari, and L. Rahman, Designing MEMS accelerometer for enhanced sensitivity and reduced cross-sensitivity in landslide monitoring. Measurement, 2024. 226: p. 114092–114099.
[2] L. Badru, J. Namaganda, and F. Okello, An IoT-Based Landslide Detection and Early Warning System in Hilly Areas. East African Journal of Information Technology, 2022. 5(1): p. 31–38.
[3] A. Wicki, P. Baumann, and D. Rickli, Assessing the potential of soil moisture measurements for regional landslide early warning. Landslides, 2020. 17(8): p. 1881–1896.
[4] S. K. Mittal, V. K. Sharma, and A. Agarwal, Design and development of an instrumentation network for landslide monitoring and the issue of early warning. Journal of Scientific and Industrial Research, 2008. 67(5): p. 361–366.
[5] G. Shanmugavadivel, P. Sivaranjani, and K. Sharmila, Detecting Communication Network Anomalies and Intrusions Using Hybrid Deep Learning. in Proc. 6th Int. Conf. Intelligent Computing and Control Systems (ICICCS). 2022. IEEE. p. 415–422.
[6] R. M. Devi, P. Anitha, and S. Jayanthi, Design of intelligent IoT for smart environmental and weather monitoring using optimal machine learning methods. International Journal of Health Sciences, 2022. 6(2): p. 13422–13434.
[7] A. Dikshit, D. N. Satyam, and I. Towhata, Early warning system using tilt sensors in Chibo, Kalimpong, Darjeeling Himalayas, India. Natural Hazards, 2018. 94(2): p. 727–741.
[8] R. Binali, M. H. T. Al-Khulaifi, and Y. Song, A Comprehensive Review on Low-Cost MEMS Accelerometers for Vibration Measurement. Journal of Molecular Engineering Materials, 2024. 12(3): p. 240–252.
[9] P. Kumar, R. Mehta, and A. Banerjee, AI-Based Climate Adaptive Farming Systems for Indian Agriculture. IEEE Access, 2023. 11: p. 49205–49218.
[10] M. Gupta, S. Sen, and P. Raj, Smart Agriculture and Climate Prediction using IoT and Machine Learning. Procedia Computer Science, 2023. 218: p. 1458–1467.
[11] T. Setiawan and R. Y. Cysela, Landslide Monitoring Using Inclinometer with MEMS Technology, in IOP Conf. Ser.: Earth and Environmental Science. 2021. 873: p. 012017.
[12] S. Mittal and D. Gupta, IoT and Edge Computing for Climate-Resilient Smart Villages: A Case Study of Rural India. Sustainability, 2023. 15(6): p. 5229–5241.

[13] M. S. Bhatia and K. Nair, Integration of IoT and AI for Disaster Management and Early Warning Systems. International Journal of Advanced Computer Science and Applications, 2022. 13(8): p. 88–96.
[14] C. Jing, H. Zhang, and X. Chen, GNSS/Accelerometer Coupled Landslide Deformation Monitoring Technology. Remote Sensing, 2022. 14(15): p. 3537–3545.
[15] S. Vimalnath, K. Madhumitha, and A. Kirubasakthi, Next-Generation Environmental Monitoring Using IoT. In Proc. 2nd Int. Conf. Artificial Intelligence and Machine Learning Applications (AIMLA). 2024. IEEE. p. 210–216.
[16] A. Pradhan, S. Chowdhury, and K. Das, LoRa-Based Wireless Sensor Network for Remote Environmental Monitoring in Hilly Terrains. IEEE Sensors Journal, 2023. 23(4): p. 5121–5130.
[17] B. Pathak, N. Ray, and M. Kar, Machine Learning-Based Prediction of Rainfall-Induced Landslides Using Sensor and Weather Data. Natural Hazards, 2024. 117: p. 297–317.
[18] Y. Yuan, C. Liu, and J. Ma, Edge-Cloud Collaborative Computing for IoT-Based Hazard Warning Systems. IEEE Internet of Things Journal, 2023. 10(2): p. 1348–1360.
[19] N. Sharma and R. Gautam, Development of Soil-Moisture Monitoring System for Precision Irrigation Using IoT. Journal of Agricultural Engineering, 2023. 60(1): p. 89–98.
[20] H. Li, Z. Wang, and Q. Chen, Weather Prediction Models Using Pressure and Humidity Trends: A Machine Learning Perspective. Applied Computational Intelligence and Soft Computing, 2022. p. 1–12.
[21] K. Singh, A. Verma, and P. Kaur, Design of Low-Cost Tilt Monitoring System for Geological Hazard Detection. Measurement Science Review, 2023. 23: p. 149–158.
[22] M. Alam and F. Hussain, A Hybrid LoRa–NB-IoT Communication Model for Real-Time Rural IoT Systems. International Journal of Distributed Sensor Networks, 2023. 19(5): p. 1–14.
[23] P. Rana, S. Tamang, and D. S. Jha, Geophone-Based Early Detection of Landslide Vibration Signatures in Himalayan Regions. Geotechnical & Geological Engineering, 2023. 41: p. 4251–4267.
[24] L. Torres and M. Estrada, IoT-Based Livestock Tracking and Geo-Fencing Using GPS and LoRaWAN. Computers and Electronics in Agriculture, 2023. 210: p. 107911–107923.
[25] T. Nguyen and R. Chandrasekar, Smart Farming Through IoT and AI: A Review of Sensor Integration, Data Analytics, and Predictive Models. Computers & Electrical Engineering, 2024. 112: p. 108840–108858.
[26] F. Carpentieri and D. O'Neill, Multisensor Fusion for Land Deformation Monitoring Using Inclinometers and MEMS Sensors. Sensors, 2023. 23(8): p. 4021–4032.
[27] J. Patel, A. Saxena, and M. Jain, Cloud-Based IoT Architecture for Environmental Monitoring Using MQTT Protocol. International Journal of Cloud Applications and Computing, 2023. 13(2): p. 52–65.