School of Computer Science Engineering and Information Systems

M.Tech (Integrated) Software Engineering

FALL 2024-2025

Project Report

IOT-BASED REAL-TIME FLOOD AND LANDSLIDE DETECTION AND MONITORING SYSTEM

SWE 1901 : Technical Answers for Real World Problems (TARP)

Offered during FALL 2024-2025

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NOVEMBER 2024

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Project Title:

IoT-Based Real-Time Flood and Landslide Detection and Monitoring System

Problem Statement:
In vulnerable regions, floods and landslides can strike suddenly, causing devastating loss of life, homes, and livelihoods. Every year, families face unimaginable risks because current detection systems lack the speed and precision to predict these natural disasters early enough for effective evacuation and response. Communities often rely on sporadic updates or limited regional monitoring, leaving many without access to life-saving information in time to act.

The **Smart Flood and Landslide Detection System** is designed to bridge this gap by providing communities with real-time, reliable insights and early warnings. By using advanced IoT sensors and predictive analytics, the system will monitor environmental changes such as rainfall, soil moisture, and terrain shifts. Through machine learning, it will anticipate potential floods and landslides, delivering timely alerts directly to local residents, emergency responders, and officials.

Our vision is to empower communities to make safer decisions and to minimize the heartache and destruction that accompany these disasters. This system aims to be a life-changing solution, offering peace of mind and the chance to protect what matters most.

Highlights

1. **Advanced IoT Integration:** Utilizes NodeMCU microcontrollers and multiple sensors (ultrasonic, soil moisture, tilt angle, and vibration) for comprehensive data collection.
2. **Real-Time Processing:** Cloud platforms like ThingSpeak enable immediate data visualization and analysis.
3. **Predictive Analytics:** Machine learning algorithms enhance the system’s ability to forecast flood and landslide events.

Here are the highlights of the **Smart Flood and Landslide Detection System** project, showcasing its key technical features:

Project Highlights

1. **IoT Integration**:
The system is built on a robust network of IoT sensors deployed in high-risk areas to continuously monitor environmental parameters like rainfall, soil moisture, temperature, and terrain stability, enhancing data accuracy and real-time responsiveness.
2. **Low-Cost Solution**:
Designed with cost-effectiveness in mind, this system utilizes affordable sensors and components, making it accessible to communities and organizations, especially in resource-limited regions.
3. **Predictive Analysis:**
Machine learning algorithms enhance the system's ability to forecast flood and landslide events.

4. **Backup Power with Solar Energy**:
Equipped with solar-powered backup, the system remains operational during power outages and extreme weather events. This ensures continuous monitoring and data collection even in critical situations.
5. **Self-Maintenance Capabilities**:
Built-in maintenance codes enable the system to automatically check for sensor malfunctions. It can diagnose issues, reducing manual checks, and improving overall reliability and efficiency.
6. **Blynk Integration for Remote Monitoring**:
Blynk integration allows real-time access and control of the monitoring system from mobile devices, enabling easy updates and remote adjustments, ideal for both users and emergency responders.
7. **Cloud Data Storage with ThingSpeak**:
The system securely stores data in the cloud using ThingSpeak, allowing for long-term analysis and trend forecasting. Historical data from floods and landslides can be reviewed to improve predictive capabilities over time.
8. **Notification and Alert System**:
The system automatically sends out alerts via SMS, emails, and in-app notifications to all registered users when potential flood or landslide indicators reach critical levels. This ensures timely and wide-reaching communication during emergencies.
9. **Early Warning and Real-Time Alerts**:
Equipped with predictive models, the system provides early alerts for evolving flood or landslide threats, giving users enough time to respond effectively and initiate preventive measures.

Abstract

In regions across the globe, communities face the relentless threat of natural disasters, particularly floods and landslides, which are often compounded by climate change. These disasters strike with little warning, disrupting lives, displacing families, and impacting infrastructure, all within moments. Early detection and rapid response are essential in preventing these disasters from becoming human tragedies. However, traditional warning systems and detection tools often fall short in terms of coverage, accuracy, and speed. There is a pressing need for solutions that not only anticipate disasters but also do so in a way that's accessible, affordable, and reliable.

The Smart Flood and Landslide Detection System seeks to fill this gap by harnessing advanced technology, predictive analytics, and real-time monitoring through a cost-effective, scalable solution. By integrating IoT (Internet of Things) sensors with predictive analytics, cloud storage, and a multi-channel alert system, this project aims to revolutionize disaster preparedness and response, particularly in high-risk areas. With a focus on community accessibility, the system has been designed to work in real time, supporting rapid, life-saving actions and ultimately building safer, more resilient communities.

Natural disasters, while sometimes inevitable, can have their impacts mitigated significantly with adequate preparation and timely warnings. In mountainous, coastal, and monsoon-affected regions, floods and landslides can be swift and deadly, often catching residents by surprise. Despite advancements in meteorological science and geological monitoring, many at-risk areas remain underserved due to the high costs, complex infrastructure, and maintenance needs associated with conventional monitoring systems.

Our project recognizes that lives depend on actionable information that is accessible, timely, and simple to interpret. In many cases, there is a critical gap between the occurrence of environmental changes—such as increased rainfall or soil moisture—and the human response to them. Our primary goal is to close this gap and offer communities reliable, round-the-clock protection. With an emphasis on low cost and high accessibility, this system has been designed for both effectiveness and scalability, ensuring that it can be adapted to a variety of regions and resource levels.

At the heart of our system lies a network of IoT sensors placed strategically in high-risk areas. These sensors continuously monitor environmental factors like rainfall, soil moisture, temperature, and terrain shifts which are parameters crucial in assessing flood and landslide risk. The IoT integration ensures that data flows seamlessly and consistently to a central database, allowing for a comprehensive and current understanding of environmental conditions. This real-time data flow is essential, as it provides an uninterrupted stream of information, capturing critical changes as they happen. This continuous monitoring system empowers the community by translating complex environmental patterns into understandable alerts, helping residents and officials respond promptly.

Next is recognizing the financial limitations. this often restrict disaster preparedness.Our system has been designed with affordability in mind. By utilizing readily available, cost-effective components, the Smart Flood and Landslide Detection System makes advanced technology accessible to even the most resource-constrained communities. The system is modular, meaning it can be scaled up or down based on the needs of each area, further enhancing its accessibility. This focus on low cost is intended to democratize safety technology, ensuring that even remote villages or low-income regions can benefit from high-quality disaster detection and response capabilities.

Disasters are unpredictable, often causing disruptions to essential services like power. This system incorporates solar power as a backup energy source, ensuring that monitoring and data collection continue uninterrupted, even during power outages. The integration of solar panels for energy supply not only makes the system more resilient during critical moments but also aligns with sustainable energy practices. In regions prone to power cuts, especially during heavy rainfall or storms, this feature guarantees that the system remains fully operational, offering communities a sense of security knowing that their monitoring system will not fail them when they need it most.

One of the main challenges with remote monitoring systems is the difficulty of regular maintenance, especially in inaccessible or hazardous locations. To address this, the system includes self-maintenance codes that actively monitor each sensor's functionality. In case a sensor malfunctions or fails to operate within expected parameters, the system alerts the technical team, allowing them to promptly address any issues before they compromise the system's reliability. This automated maintenance feature not only minimizes downtime but also reduces the need for constant manual inspections, making the system both more efficient and dependable.

The Blynk mobile application serves as a powerful tool for remote monitoring, giving users—whether residents, local officials, or disaster response teams—real-time access to the system's data. Through the app, users can receive live updates, check the status of sensors, and adjust settings as needed. The convenience of having critical information at one's fingertips is invaluable during emergencies, enabling quicker and more informed decision-making. By integrating Blynk, the system brings disaster preparedness into the hands of those who need it most, creating a sense of control and empowerment in vulnerable communities.

Storing data in the cloud has several advantages, particularly for long-term analysis and predictive modeling. With ThingSpeak cloud integration, the system archives environmental data, which can be accessed and analyzed to better understand trends over time. By maintaining a historical record of rainfall, soil shifts, and other environmental changes, the system can provide insights into seasonal patterns and evolving risk levels. This information is vital not only for immediate disaster response but also for long-term planning and preparation. Cloud storage thus serves as a knowledge base, aiding researchers, government officials, and disaster response teams in building more robust and data-driven prevention strategies.

The Notification and Alert System is a critical feature, as it transforms raw data into actionable information. When environmental parameters reach predefined thresholds, the system automatically triggers alerts via multiple channels: SMS, email, and in-app notifications. By delivering timely, clear, and direct alerts, the system ensures that people receive essential warnings with minimal delay. This feature is especially important in areas where connectivity may be limited, as SMS ensures alerts reach users even if they have limited internet access. For communities, this means receiving crucial, life-saving information without the need for constant monitoring, allowing them to focus on response rather than data interpretation.

Beyond real-time monitoring, the system includes early warning features that leverage machine learning models to predict potential threats. By analyzing patterns and trends in the environmental data, the system can forecast risks before they reach critical levels. This early alert capability provides communities and responders with additional lead time to mobilize resources, evacuate at-risk areas, and implement preventive measures. The inclusion of predictive analytics represents a major step forward in disaster preparedness, transforming the system from a reactive tool to a proactive solution capable of minimizing disaster impacts before they occur.

Our System is designed not only as a technical solution but as a community asset. Its low-cost, accessible nature makes it ideal for deployment in underserved areas where traditional monitoring systems are too costly or complex to implement. By giving communities access to critical data and timely warnings, the system empowers residents to make informed decisions about their safety. For local governments and NGOs, it provides a reliable, scalable tool to support disaster response and preparedness initiatives, helping to build more resilient infrastructure and communities.

In real-world applications, this system could save countless lives by providing communities with the lead time they need to evacuate, protect their assets, and avoid high-risk zones. Whether it’s a remote village in a mountainous region or a densely populated coastal area, the Smart Flood and Landslide Detection System adapts to different environments, enhancing the safety and peace of mind of those who need it most.

1. Introduction

1.1 Background Information of the Work

Floods and landslides are two of the most common and destructive natural disasters, causing significant loss of life and property worldwide. According to the World Meteorological Organization (WMO), floods account for 47% of all weather-related disasters, impacting millions of people each year. Landslides, often triggered by heavy rainfall or rapid snowmelt, pose similar threats, leading to devastating consequences in mountainous and hilly regions. Climate change has further exacerbated the frequency and intensity of these events, making effective monitoring and early warning systems essential for disaster management.

Traditional methods of monitoring floods and landslides have relied heavily on manual data collection, which often results in delays and inaccuracies. Meteorological agencies have utilized weather stations and satellite imagery to assess conditions, but these systems frequently lack the granularity required for localized events. Recent advancements in sensor technology and data analytics have paved the way for more robust solutions, particularly through the integration of the Internet of Things (IoT). IoT technologies allow for real-time data collection and analysis, enabling stakeholders to make informed decisions in emergency situations.

This project focuses on developing an IoT-based system that utilizes a network of sensors to monitor environmental conditions and provide timely alerts for potential floods and landslides. By leveraging low-cost sensors and cloud computing, the system aims to offer a comprehensive and accessible solution to communities vulnerable to these disasters.

Landslides are a major natural hazard with severe impacts on life and infrastructure. Traditional prediction methods are slow and resource-intensive. Advances in data collection and machine learning now enable a more efficient, real-time approach to landslide prediction, leveraging environmental and geological data to provide early warnings.

1.2 Need of the Work

The need for an effective flood and landslide detection and monitoring system is underscored by the increasing frequency of these disasters due to climate change, urbanization, and land degradation. In many regions, existing monitoring systems are outdated, lack integration, and fail to provide real-time data. As a result, communities are left unprepared for sudden disasters, leading to avoidable loss of life and property.

The consequences of inadequate monitoring are particularly evident in developing countries, where resources for disaster management are limited. In these areas, the implementation of low-cost, accessible technologies can significantly enhance disaster preparedness and response capabilities. Furthermore, as urban areas continue to expand into vulnerable regions, the risk of floods and landslides increases, necessitating proactive measures to safeguard populations and infrastructure.

This project addresses these pressing needs by proposing an IoT-based system that can provide real-time monitoring, predictive analytics, and community engagement. By delivering timely alerts and critical information, the system aims to empower communities to take preventive actions and respond effectively to impending disasters.

With climate change increasing landslide risks, there's a critical need for accurate and scalable predictive systems. Machine learning models can offer rapid, reliable detection, providing a proactive solution to mitigate the impacts of landslides.

1.3 Contribution Made to the Work

This project brings a fresh, community-focused approach to disaster management by addressing two of the most common and interconnected natural threats: floods and landslides. By integrating these hazards into a single system, it offers a comprehensive solution capable of assessing both risks, which often occur together, particularly in monsoon-prone or mountainous regions. Recognizing this relationship, the project combines a range of sensors—each designed to monitor critical environmental factors that signal the potential for either or both disasters.

To monitor flood risks, ultrasonic sensors are used for real-time water level tracking, while rainfall sensors gauge precipitation intensity. For landslide detection, soil moisture sensors and tilt sensors assess soil saturation and slope stability, while vibration sensors detect ground movement, capturing shifts that may indicate landslides. Additionally, temperature and humidity sensors monitor atmospheric conditions, and solar panels provide a sustainable power backup, ensuring the system remains operational during critical moments. An LCD I2C screen offers manual on-site readings, making it accessible to local residents and responders alike.

Leveraging cloud computing, the project integrates with platforms like ThingSpeak, enabling data processing and visualization in real-time. Through this cloud-based setup, stakeholders can access environmental information remotely, track data trends, and make informed decisions, regardless of their location. This remote access transforms situational awareness, allowing for rapid action in the face of emergencies.

To enhance forecasting, machine learning algorithms analyze historical data alongside live sensor input. This predictive layer improves the accuracy of flood and landslide warnings, helping communities stay a step ahead and reducing false alarms—a critical factor in building trust among those who depend on this system for safety.

This study implements and evaluates machine learning models, including Logistic Regression, Random Forest, and XGBoost, to predict landslides. Key contributions include:

- Data Enhancement: Preprocessing and feature engineering to improve data quality.
- Class Imbalance Handling: Using SMOTE and ADASYN for balanced model training.
- Model Evaluation: Detailed comparison of models using accuracy, precision, and recall to identify the best approach.

1.4 Organization of the Paper / Report

This report is structured to provide a comprehensive overview of the IoT-Based Real-Time Flood and Landslide Detection and Monitoring System, detailing its development, implementation, and impact.

- **Section 1** introduces the background of the work, the need for the proposed system, its contributions, and the organization of the report.
- **Section 2** presents a literature review, summarizing existing methods and technologies for flood and landslide detection, highlighting their strengths and weaknesses, and comparing them to the proposed system.
- **Section 3** outlines the proposed methodology, including the system architecture, hardware and software requirements, and module illustrations. Diagrams will illustrate the overall system design and the role of each component.
- **Section 4** discusses the experimental study, detailing the experimental setup, presenting results in tables and graphs, and providing a comprehensive discussion of the findings. The results will be compared with existing systems to demonstrate the efficacy of the proposed solution.
- **Section 5** concludes the report by summarizing the key findings, discussing the implications of the work, and outlining future research directions and potential improvements to the system.

2. Literature Review

LITERATURE SURVEY

Serial Number	Title and Year	Gaps Identified
1	Artificial Intelligence-Integrated Water Level Monitoring System for Flood Detection Enhancement (2024)	- Dependency on solar power. - Image quality and processing. - Network connectivity. - Maintenance requirements. - Scalability issues. - Data privacy and security
2.	IoT-Driven Microseismic Sensing System and Monitoring Platform for Landslide Detection (2024)	-Sensors may not always provide accurate or frequent data. -Data might be delayed or inconsistent. -The system needs to cover more areas. -Sensors need better calibration and reliability.

3.	A comparative evaluation of landslide susceptibility mapping using machine learning-based methods in Bogor area of Indonesia(2024)	- No consensus on the best ML algorithm for LSM. - Some ML models, like Decision Tree (DT), underperform compared to others. - Ensuring the quality and representativeness of landslide and non-landslide points is crucial.
4	Flood Detection with SAR: A Review of Techniques and Datasets (2023)	- Vegetated and urban areas. - Lack of standard procedures. - Need for joint efforts. - Limited validation practices
5	A Novel Approach for a Smart Early Flood Detection and Awareness System using IoT (2023)	- Dependency on internet connectivity. - Power supply issues. - Sensor limitations. - High initial setup cost. - Maintenance requirements. - Data privacy concerns
6	Automatic Flood Detection from Sentinel-1 Data Using a Nested UNet Model and a NASA Benchmark Dataset (2023)	- Polarization variability. - Geographic transferability. - Data specificity. - Environmental complexity
7	Flash Flood Detection via Copula-Based Intensity–Duration–Frequency Curves: Evidence from Jamaica (2023)	- Exclusion of other factors. - Specificity to Jamaica. - Data limitations. - Climate change considerations
8	Flood Monitoring by Integration of Remote Sensing Technique and Multi-Criteria Decision Making Method (2022)	- Dependence on satellite data. - Case study specificity. - Exclusion of certain factors. - Computational complexity
9	Design of IoT Based Flood Monitoring and Alerting System (2022)	- Dependence on wireless connectivity. - Limited to certain flood incidents. - Potential for false alarms. - Initial setup cost. - Maintenance requirements
10	A Real-Time Flood Detection System Based on Machine Learning Algorithms with Emphasis on Deep Learning (2021)	- Performance variability. - NLP techniques impact. - Economic constraints

11	Flood Detection and Warning System (FLOWS) (January 2018)	- Data transfer delay. - Message capacity. - Application functionality. - System integration
12	Flood Prediction Using Rainfall-Flow Pattern in Data-Sparse Watersheds (2023)	- Limited data affects accuracy. - Effectiveness varies with conditions
13	Monitoring Slope Movement and Soil Hydrologic Behavior Using IoT and AI Technologies: A Systematic Review (2024)	-Combining different technologies can be challenging. -Real-time data processing might be slow. -Better strategies are needed to adapt to changes. -Some important soil factors may not be monitored fully.
14	IoT Based Landslide Detection System (2024)	- Sensors may not always be accurate or durable. - There could be delays in sending and processing data. - Risk of false alarms or missing detections. - Future improvements should focus on better sensors and data analysis.
15	IoT-enabled landslide detection mitigating environmental impacts (2024)	- Existing works primarily focus on vibration sensors. - Insufficient real-time data from slope movement sensors. - Lack of integration of rainfall and soil moisture sensors.
16	Prototype of an IoT-Based Low-Cost Sensor Network for the Hydrological Monitoring of Landslide-Prone Areas (2023)	- High cost of current monitoring devices. - Lack of affordable, widespread hydrometeorological data collection methods. - Insufficient long-distance communication solutions.
17	An Ensemble Learning-Based Experimental Framework for Smart Landslide Detection, Monitoring, Prediction, and Warning(2023)	- Inefficiency of existing prediction techniques. - High cost of current monitoring tools. - Absence of early warning or forecast capabilities.. - Limited applicability for emergency situations.
18	IoT-Based Landslide Detection and Indication(2023)	- Difficulty in prompt response to data changes. - Challenges in real-time data transmission to the analysis center. - Limited applicability for emergency situations.
19	IoT-Based Landslide Detection and Monitoring(2022)	- Need for real-time landslide detection and monitoring. - Lack of timely alerts for effective disaster response. - Insufficient comprehensive data for risk reduction.

20	An IoT Based Landslide Monitoring and Fuzzy Logic Driven Early Warning System (2022)	- The system might not work well in all environments. - Fuzzy logic models may need more accuracy. - Integration with other technologies could be improved. - Future work should expand sensor types and refine models.
21	Robust Early Detection Mechanism for IoT Enabled Landslide Monitoring using LoRa Technology (2020)	-- Expanding the network can be challenging. - Machine learning integration needs improvement. - The data transmission range might be limited. - Future work should improve network coverage and machine learning accuracy.
22	An information quantity and machine learning integrated model for landslide susceptibility mapping in Jiuzhaigou, China(2024)	- No standard method for non-landslide samples. - Relies on subjective expert judgment. - Random selection may not ensure low susceptibility.
23	Aerial imagery segmentation of natural disaster-affected areas using deep convolutional networks for disaster assessment (2024)	- The study doesn't address potential inaccuracies or the need for more frequent data from sensors. - There is no mention of possible delays or inconsistencies in the data collection process. - The system needs to be expanded to cover larger and more diverse areas.
24	SE-YOLOv7 Landslide Detection Algorithm Based on Attention Mechanism and Improved Loss Function	- Existing algorithms have low precision and weak generalization in landslide detection. - Need for improved algorithms to enhance detection accuracy. - Lack of extensive validation across diverse regions and landslide types. - Ensuring the model's effectiveness in real-world scenarios requires further testing.
25	Landslide Detection from Open Satellite Imagery Using Distant Domain Transfer Learning	- Limited diversity and size of landslide image datasets. - for comparison with more state-of-the-art models. - Ensuring the model is computationally efficient for large-scale applications.
26	Landslide susceptibility zonation using integrated supervised and unsupervised machine learning techniques in the Bhagirathi Eco-Sensitive Zone (BESZ), Uttarakhand, Himalaya, India	- Existing algorithms often exhibit low precision in landslide detection. - current models have weak generalization capabilities. - Limited variety and size of landslide image datasets. - Lack of comprehensive comparison with state-of-the-art models.
27	Landslide detection in the Himalayas using machine learning algorithms and U-Net	- Need to improve computational efficiency for large-scale applications. - in addressing varying environmental conditions affecting model accuracy. - automation levels for the entire landslide detection pipeline.

		- Insufficient field validation to verify model predictions.
28	Landslide Detection Using Machine Learning Algorithms	- Current methods may lack precision. - use of real-time data and advanced technologies. - Need for better adaptability to different conditions.
29	Hybrid machine learning approach for landslide prediction, Uttarakhand, India	- Limited number of landslide and non-landslide samples may affect model robustness. - Some relevant factors might be missing from the analysis. - Models use static data, missing temporal changes like weather or land use. - Models tested only in Uttarkashi; performance in other regions needs validation.
30	Deep learning-based landslide susceptibility mapping	- Integration with real-time data could improve prediction accuracy. - Limited comparison with non-hybrid models could be expanded. - GIS platform's scalability and ease of use for non-experts need assessment.

Admad Fedzil Ismail et al. [1] introduced a water level monitoring system leveraging AI to enhance flood detection. The system addresses issues such as dependency on solar power, image quality, network connectivity, and data privacy. Future work includes expanding the system, improving image processing, integrating with other IoT systems, and using machine learning for predictive analysis .

Indukala et al. [2] introduced a cutting-edge microseismic sensing system tailored for landslide detection. By integrating IoT technology with microseismic sensors, the study presented a robust platform that significantly improved real-time detection and monitoring. The system's innovative approach aimed to provide timely alerts and enhance the overall effectiveness of landslide management.

Melati et al. [3]evaluated various machine learning models for landslide prediction using metrics such as accuracy, precision, sensitivity, specificity, and F1-score. The study utilized ROC curves and confusion matrices to assess model performance, highlighting the importance of validation in selecting the best model for reliable landslide detection.

Donato Amitrano et al.[4] reviewed various techniques and datasets for flood detection using Synthetic Aperture Radar (SAR). They identified challenges such as monitoring in vegetated and urban areas, lack of standard procedures, and limited validation practices. Future research should focus on new SAR missions, improved validation tools, promoting reproducibility, and exploring GNSS-R technology .

L. Saravanan et al.[5] proposed a smart early flood detection and awareness system using IoT, addressing issues like sensor accuracy, real-time data processing, and system integration. Future improvements include enhancing sensor accuracy, integrating additional data sources, and expanding system scalability .

Binayak Ghosh et al. [6]developed an automatic flood detection system using Sentinel-1 data with a nested UNet model. They discussed challenges related to model accuracy and data quality. Future work should focus on improving model robustness, integrating additional data sources, and enhancing real-time processing capabilities .

Dino Collalti et al.[7] employed copula-based intensity–duration–frequency curves for flash flood detection in Jamaica. The study highlighted challenges in data availability and model accuracy. Future research should focus on improving data quality, refining models, and expanding applicability to different regions .

Hadi Farhadi et al.[8] integrated remote sensing techniques with multi-criteria decision-making methods for flood monitoring. They highlighted the challenges of integrating diverse data sources and the need for improved decision-making algorithms. Future work should focus on enhancing data integration techniques and refining decision-making models .

Emil Daniel Maer and Adrian Augustin Pop**Error! Reference source not found.** explored, Design of IoT Based Flood Monitoring and Alerting System highlighting challenges in Dependence on wireless connectivity, Potential for false alarms .

Abdirahman Osman Hashi et al. [10]developed a real-time flood detection system utilizing machine learning and deep learning algorithms. They noted challenges such as computational requirements and data availability. Future research should aim at optimizing algorithms and improving data collection methods .

Syahaneim Marzukhi et al. [11]presented FLoWS, a flood detection and warning system, emphasizing real-time data processing and network connectivity. Challenges include system scalability and integration with existing infrastructure. Future work involves enhancing system robustness and expanding its deployment .

Yuelong Zhu et al. [12]developed a flood prediction model using rainfall-flow patterns in data-sparse watersheds, identifying gaps in data availability and model accuracy. Future research should focus on improving data collection, refining prediction algorithms, and expanding model applicability to various watersheds .

M J B Alam et al. [13]presented a comprehensive review that delved into various methodologies for monitoring slope stability and soil hydrology through IoT and AI technologies. The paper discussed the integration of soil moisture, matric suction, and slope movement data to predict and mitigate landslide risks. It emphasized how advancements in these technologies were crucial for effective landslide management.

Om Narkhede et al. [14]focused on an IoT-based landslide detection system that used a range of sensors to monitor environmental conditions. By leveraging real-time data and cloud technologies, the system enhanced the speed and accuracy of landslide detection. The study highlighted the system's potential to improve response times and minimize damage through timely alerts.

K. Arun et al. [15]explored an IoT-based landslide detection system designed to address the increasing frequency of rainfall-induced landslides in India. The system uses rainfall measurement and soil moisture sensors, alongside vibration and slope movement sensors, to improve data precision and integration. The primary goal was to enable early evacuation of landslide-prone areas, thereby saving lives. The system also sent warning alerts to disaster management authorities, presenting significant advancements in early detection and minimizing environmental impacts through proactive evacuation measures.

Marino P et al. [16]developed a prototype low-cost IoT-based monitoring network aimed at expanding hydrological data collection in landslide-prone areas. The study focused on the slopes of Cervinara, Italy, where landslides frequently occur. The network used low-cost capacitive sensors for soil moisture measurement, communicating through a Wi-Fi-based IoT system. The ThingSpeak platform enabled remote data visualization. The prototype demonstrated the potential for affordable hydrometeorological monitoring, suitable for early warning systems in landslide-prone regions, thus promoting environmental sustainability and risk management.

Sharma et al. [17]proposed an innovative, low-cost IoT-based system for landslide detection, monitoring, prediction, and warning. The system utilized MEMS-based sensors to measure soil moisture and movement, providing real-time data compared against threshold values. The ensemble learning-based risk prediction model demonstrated high accuracy, precision, and recall rates. The system sent alert SMS notifications to relevant authorities, enhancing landslide prediction technologies and enabling better real-time monitoring. The approach aimed to advance wireless sensor networks for emergency applications, offering significant improvements in landslide risk management.

Pranav K et al. [18]developed an IoT-based landslide detection system focusing on real-time data transmission and early warning. The system employed accelerometer and soil moisture sensors to monitor ground movement and moisture levels, respectively. It utilized wireless sensor nodes and the MQTT protocol for efficient data transmission and alert distribution. The study highlighted the system's reliability, cost-effectiveness, and delay efficiency. Future enhancements included adopting the LoRa model for long-distance communication, aiming to improve performance and scalability, thus contributing to the real-time monitoring and risk assessment of landslides.

Vishakha S et al.[19] developed an IoT-based landslide detection and monitoring system designed to provide timely alerts and comprehensive data for effective response and risk reduction. The system integrated accelerometers, inclinometers, and moisture sensors to monitor ground movement, slope stability, and soil conditions in real-time. Connected to a central IoT gateway, the system collected, processed, and analyzed data using machine learning algorithms to detect potential landslide events. The system sent alert messages via GSM to relevant authorities, enhancing disaster management strategies and contributing to the safety and resilience of affected regions.

Felix HARERIMANA et al. [20]introduced a fuzzy logic-based early warning system for landslide prediction using IoT technology. The system employed various sensors to monitor soil and slope conditions, applying fuzzy logic to enhance prediction accuracy. The study emphasized the importance of early warnings in mitigating landslide impacts.

Prof. Mala P et al.[21] proposed a novel landslide detection framework utilizing LoRa technology. The system's modular design and low-cost implementation provided a reliable solution for landslide monitoring. The paper discussed future enhancements, including machine learning integration and expanded LoRa networks, to improve prediction accuracy and response.

Yang et al. [22]developed a landslide susceptibility mapping (LSM) model using the IQ-ML approach, which improves resource efficiency by focusing on high-risk areas and provides comprehensive coverage for administrative regions. The study applied this model to identify new landslide-prone areas in Jiuzhaigou post-earthquake and highlighted the need for further research into data-scarce areas to enhance model accuracy and application.

Nugraha et al. [23]applied deep convolutional networks for semantic segmentation of aerial imagery from natural disasters. The PSPNet model outperformed others, achieving high accuracy and precision in identifying and classifying affected areas. The study also implemented a Fuzzy C-Means clustering algorithm for detailed disaster assessment and plans to develop a comprehensive disaster management system for improved response and recovery.

Qing Liu et al. [24]developed the SE-YOLOv7 model for landslide detection using Google Earth images. This model, enhanced with the SE attention mechanism and VariFocal loss function, showed superior performance in detecting landslides compared to YOLOv7, YOLOv4, and Faster R-CNN, with higher metrics in mAP, Precision, Recall, and F1-Score. Despite its effectiveness, the study acknowledged the challenges in handling diverse landslide morphologies and the need for further improvements in detection accuracy and classification.

Hengwu Qin et al [25] introduced the DDTL algorithm for landslide detection using remote sensing images and DEM data. The study combined DDTL with an improved attention mechanism, CBAM, and demonstrated its effectiveness compared to other methods. The DDTL model, which does not require training and testing data to have the same distribution, achieved better classification performance with the NWPU-RESISC45 dataset. The study acknowledged limitations such as high computational costs and the need for larger, publicly available landslide datasets.

Meenakshi Devi et al. [26]developed landslide susceptibility zonation maps for Bhagirathi Valley using machine learning methods RF, XGBoost, and KNN combined with the ISODATA clustering technique. The study found that 37–48% of the area is in high to very high susceptibility zones, particularly along major drainage and roads. XGBoost showed the highest AUC (0.89) but had overestimation issues, while RF was identified as the most efficient model for landslide prediction based on consistent performance and better identification of susceptibility zones.

Sansar Raj Meena et al. [27]investigated the impact of patch size on the performance of machine and deep learning models for landslide detection using U-Net and other algorithms. The study compared models trained with patch sizes ranging from 16 × 16 to 256 × 256 pixels and found that smaller patches generally yielded better results. The U-Net model with a 16 × 16 pixel patch size, combined with a learning rate of 0.001, outperformed others in accuracy. The study also highlighted challenges with false positives due to topographical influences and suggested that the optimal patch size and model parameters significantly affect detection performance

Devi Naveen et al.[28] evaluated the use of SMOTE for balancing datasets in machine learning by generating synthetic data to reduce duplication and improve storage efficiency. The study emphasized the importance of data preparation, including maintaining clean and relevant data, and the role of Geographic Information Systems (GIS) in managing spatial data. the use of SMOTE in creating synthetic binary classification datasets and tested the model with repeated stratified k-fold cross-validation. The study also discussed the confusion matrix's role in evaluating model predictions, highlighting the challenges of false positive generation.

Poonam Kainthura et al.[29] evaluated landslide prediction in the Uttarkashi region, highlighting the importance of accurate modeling due to the area's fragile geological formations. The study compared five hybrid machine learning techniques for assessing landslide risk and found that the XGBoost-based rough set approach achieved the highest accuracy (89.92%). This method outperformed others by optimizing individual models and improving prediction capability.

Mohammad Azarafza et al. [30]applied a novel CNN–DNN model for landslide susceptibility mapping in Isfahan province, Iran. The CNN–DNN model achieved high accuracy (AUC = 90.9%; IRs = 84.8%) and outperformed various benchmark approaches such as SVM, LR, GNB, MLP, BNB, and DT. It also showed superior error metrics (MSE = 0.17, RMSE = 0.40, MAPE = 0.42) compared to other models. The CNN component of the model effectively utilized the spatial characteristics of landslides, predicting high-susceptibility zones aligned with regional geological trends. The study recommends the CNN–DNN approach for its precision in landslide susceptibility mapping

3.METHODOLOGY

The methodology focuses on utilizing IoT sensors and communication protocols to detect and monitor flood and landslide-prone areas in real time. The system will alert concerned authorities and citizens to prevent loss of life and property. Below is the step-by-step methodology:

Flood Detection:

1. **Hardware Setup**:
   - NodeMCU(ESP-32) is used as the primary microcontroller.
   - Ultrasonic sensors are deployed to measure water levels.
   - Rainfall measurement sensors are integrated to monitor precipitation.

- Humidity and Temperature Monitoring sensor is used to continuously recording the environmental conditions, Sudden changes in humidity and temperature can signal severe weather changes that could lead to floods.
- Data from sensors are sent to cloud platforms like ThinkSpeak and mobile apps like Blynk for real-time monitoring.

2. **Process**:
   - The ultrasonic sensor continuously monitors water levels ,Rain sensor monitors the rain and Humidity&Temperature sensors monitors the humidity and temperature of the environment.
   - When water reaches a critical threshold, a warning is triggered.
   - Rain sensor provide updates at regular interval based on the amount of rainfall .
   - The system sends alerts via the ThinkSpeak cloud platform and a popup warning message through the Blynk app.

Landslide Detection:

1. **Hardware Setup**:
   - Node MCU is again used for monitoring.
   - Soil moisture sensors detect the moisture content in the soil.
   - Tilt angle sensors monitor the slope stability.
   - Vibration sensors detect ground movement and potential landslide risks.

2. **Process**:
   - The soil moisture sensor captures moisture levels to predict landslides.
   - Tilt angle sensors detect deviations in slope stability.
   - Vibration sensors capture ground shifts and vibrations.
   - When anomalies are detected, an immediate warning is sent to alert users.

3.1 DETAILED ARCHITECTURE

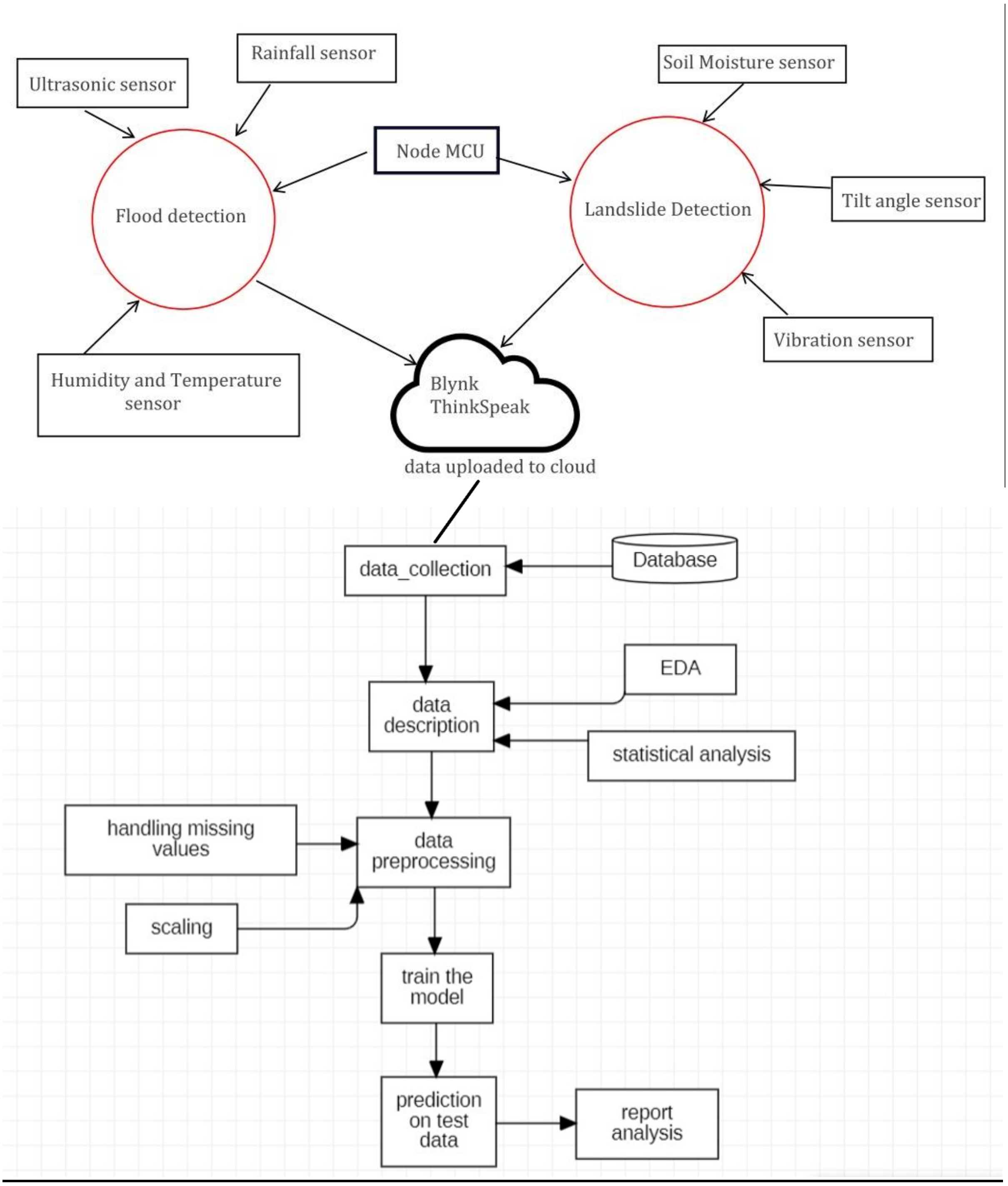
The architecture consists of two main subsystems: the flood detection system and the landslide detection system. Each system is connected to the NodeMCU microcontroller, which communicates with the cloud server for real-time data monitoring and provides notification.

1. Sensor Module

The Sensor Module is a critical component of the Smart Flood and Landslide Detection System, responsible for real-time data collection from the environment. It incorporates various sensors, including water level sensors (such as ultrasonic sensors), soil moisture sensors, and rainfall sensors. These sensors continuously monitor environmental conditions and provide crucial data to the microcontroller. The collected data is analyzed to detect potential flood or landslide events based on predefined thresholds. This module serves as the foundation for ensuring timely alerts and informed decision-making.

2. Machine Learning Module

The Machine Learning (ML) Module enhances the Smart Flood and Landslide Detection System by analyzing historical and real-time data to improve prediction accuracy. Using algorithms trained on past environmental data, the ML module can identify patterns and trends that indicate an increased risk of floods or landslides. This module processes data from the Sensor Module, applying predictive models to assess the likelihood of adverse events occurring. By integrating machine learning, the system can provide more reliable forecasts and timely alerts, ultimately aiding in disaster preparedness and response efforts.



3.2 Hardware Requirements:

-For Landslide Detection

1. **Microcontroller**: NodeMCU(ESP 8266)
2. **Sensors**:
    - Soil Moisture Sensor for landslide risk assessment
    - Tilt Angle Sensor for slope stability analysis
    - Vibration Sensor for detecting ground movement
3. **Power Supply**: mains and solar panel as backup
4. **Breadboard** and **jumper wires** for circuit connections

-For flood detection

1. **Microcontroller**: NodeMCU(ESP 32)
2. **Sensors**:
   - Ultrasonic sensor for waterlevel measurement,
   - Rainfall measurement sensor for measuring intensity of rainfall
   - Humidity and temperature sensor for measuring environmental humidity and temperature
3. **Power Supply**: mains and solar panel as backup
4. **Breadboard** and **jumper wires** for circuit connections

Software Requirements:

ARDUINO IDE for coding NodeMCU

Development Environment: Google Colab

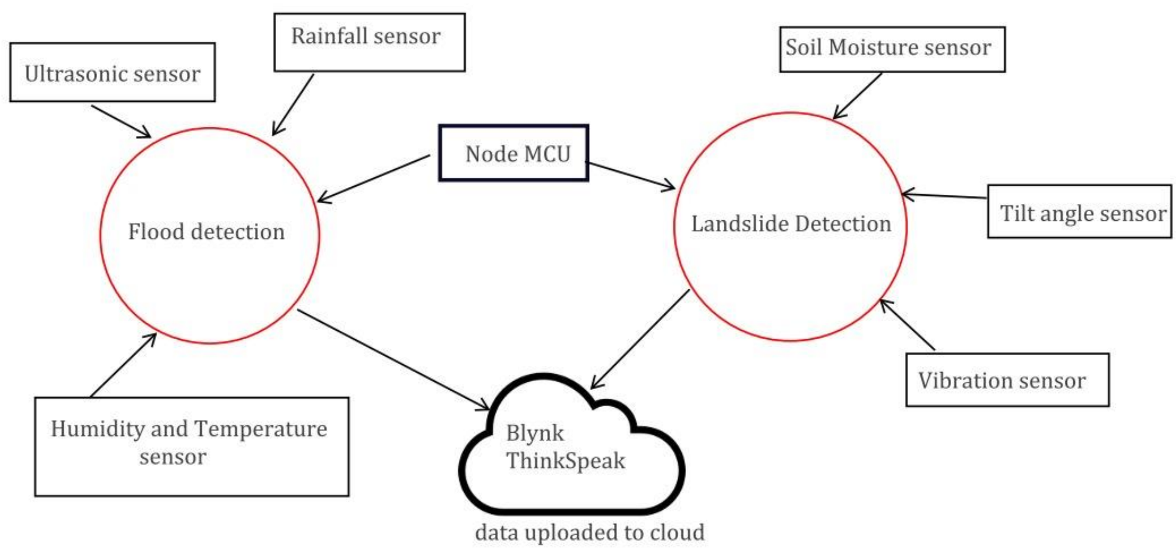
Libraries: pandas, scikit-learn, xgboost, imblearn, matplotlib, seaborn

Operating System: Windows/Linux/MacOS

3.3 Module Illustrations

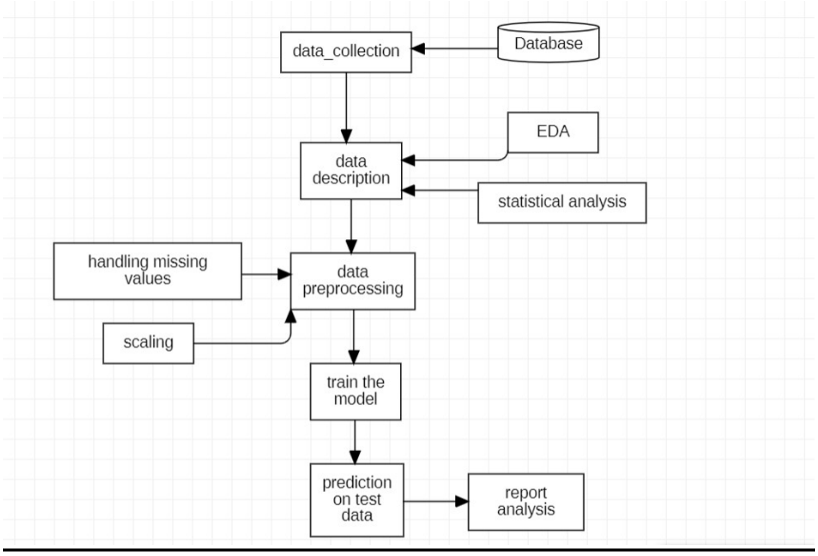
Module 1: Sensor Module

- **Function:** Collects environmental data (water level, soil moisture, rainfall).
- **Components:** Sensors connected to the microcontroller.



Module 2: Data Processing Module

- **Function:** Processes the sensor data to detect potential floods or landslides.
- **Components:** Microcontroller with connected sensors and power supply.



Module 3: User Interface and Notifications Module(Blynk)

- **Function:** Displays real-time data and alerts.
- **Components:** Web dashboard or mobile application.
- **Illustration:** Screenshots or mockups of the UI showing data visualization.

FOR ML BASED LANDSLIDE DETECTION :

- **Data Preprocessing Module**: Cleans and prepares the dataset, handling missing values and normalizing features.
- **Model Training Module**: Implements machine learning algorithms (Logistic Regression, Random Forest, XGBoost) with oversampling techniques like SMOTE and ADASYN.
- **Prediction Module**: Makes predictions on test data and outputs landslide occurrence likelihood.
- **Evaluation Module**: Analyzes model performance using accuracy, precision, recall, and F1-score.

3.4. Example

Example Scenario:

- **Situation:** A heavy rain event is detected, causing water levels to rise.
- **Process:**
    1. The rainfall sensor detects excessive rainfall.
    2. The water level sensor measures an increase in water level.
    3. The microcontroller processes this data and determines that the water level has exceeded the predefined threshold.
    4. The system triggers the communication module to send an alert via SMS to the registered users and updates the web dashboard.
    5. Users receive notifications on their devices about the potential flood risk.

4.Experimental Study

4.1 Experimental Setup for landslide module

The experimental setup for the IoT-based real-time landslide detection system involved using a NodeMCU microcontroller to gather data from various sensors placed in a landslide-prone area. The sensors utilized in this study include:

- **Soil Moisture Sensor:** Measures the moisture content of the soil, which is critical for assessing landslide risk.
- **Tilt Angle Sensor:** Monitors the slope's angle to detect any instability.
- **Vibration Sensor:** Detects ground movement that may indicate potential landslide activity.

The NodeMCU is connected to these sensors and sends data to a cloud platform (e.g., ThingSpeak) for real-time processing and analysis. The setup allows continuous monitoring of environmental conditions that contribute to landslide risks.

FOR ML BASED LANDSLIDE DETECTION :

- **Objective**: To predict landslide occurrences by training and testing machine learning models on geological and environmental data.
- **Dataset**:
    - **Description**: A dataset containing features like soil moisture, rainfall, slope angle, and elevation, with the target variable indicating landslide occurrence (1) or non-occurrence (0).
    - **Preprocessing**: Data cleaning, handling missing values, and feature scaling are applied. SMOTE or ADASYN is used to balance the target variable classes.
- **ABOUT DATA:**

Data dictionary for landslide identification dataset

- **1. CELLID**

1	6	11	16	21
2	7	12	17	22
3	8	13	18	23
4	9	14	19	24
5	10	15	20	25

- Each sample is composed of data from 25 cells, covering an area of 625 m^2. Each cell represents an area of 5 x 5 m^2 and has nine features (as introduced in section 2). For a landslide sample, cell 13 is the location of landslide, and other cells are the neighboring areas. For a non-landslide sample, there is no recorded landslide occurrence within the sample area.

- **FEATURE DICTIONARY**

Feature name	Data type	Description
CELLID_elevation	Continuous	Digital elevation of the terrain surface in meter

CELLID_slope	Continuous	Angle of the slope inclination in degree
CELLID_aspect	Continuous	Exposition of the slope in degree
CELLID_placurv	Continuous	Planform curvature, curvature perpendicular to the direction of the maximum slope
CELLID_procurv	Continuous	Profile curvature, curvature parallel to the slope, indicating the direction of maximum slope
CELLID_lsfactor	Continuous	Length-slope factor that accounts for the effects of topography on erosion
CELLID_twi	Continuous	Topographic wetness index, an index to quantify the topographic control on hydrological process
CELLID_geology	Categorical	Lithology of the surface material 1: Weathered Cretaceous granitic rocks 2: Weathered Jurassic granite rocks 3: Weathered Jurassic tuff and lava 4: Weathered Cretaceous tuff and lava 5: Quaternary deposits 6: Fill 7: Weathered Jurassic sandstone, siltstone and mudstone
CELLID_sdoif	Continuous	Step duration orographic intensification factor: an index to quantify the amplification of orography on rainfall
Label	Categorical	1: Landslide 0: Non-landslide

- **Model Selection**: Several machine learning algorithms are evaluated, including Logistic Regression, Random Forest, and XGBoost.
- **Evaluation Metrics**: Models are assessed on accuracy, precision, recall, and F1-score to determine the most reliable predictor.
- **Tools**:
    - **Development Environment**: Google Colab
    - **Libraries**: pandas, scikit-learn, xgboost, imblearn for oversampling, and visualization tools like matplotlib and seaborn.

COLAB LINK :

https://colab.research.google.com/drive/14KxmVrHCbaswhMrQlDiNEa7m0Uv1XwZ4?usp=sharing

MODEL	ACCURACY	PRECISION	RECALL(SENSITIVITY)	F1 SCORE
XG BOOST	86	0-89 1-75	93 64	91 69
RANDOM FOREST	86.8	0-88 1-81	95 61	91 69
LOGISTIC REGRESSION	83.02	0-85 1-74	94 49	89 59
GRADIENT BOOSTING	85	0-87 1-75	93 59	90 66
Random Forest with PCA	83	0-82 1-86	98 37	89 52
LOGISTIC REGRESSION WITH PCA	82	0-84 1-72	94 47	89 57
BAGGING (base estimator as LR)	83	0-85 1-74	94 51	89 60
Assemble learning (bagging with random forest, xgboost)	RF : 85.9 XG: 85.8 ENSEMBLE: 86.25	0-88 1-78	94 63	91 70
RANDOM FOREST(SMOTE)	84	0-91 1-67	88 73	89 69
XG BOOST (SMOTE)	89	0-90 1-68	89 69	89 69
LOGISTIC REGRESSION(SMOTE)	77	0-91 1-51	76 76	83 62
RANDOM FOREST(ADASYN)	84.3	0-91 1-67	88 73	89 70
LOGISTIC REGRESSION(ADASYN)	76	0-91 1-51	75 78	82 62
XG BOOST (ADASYN)	84.58	0-90 1-68	89 72	90 70
GRADIENT BOOSTING(SMOTE)	82	0-92 1-60	82 80	87 69
GRADIENT BOOSTING(ADASYN)	82	0-93 1-60	81 80	87 68

4.3 Results and Discussion(landslide detection)

The data collected over the monitoring period indicates a clear correlation between soil moisture levels, tilt angle, and vibration readings with the occurrence of landslides. For instance:

- **Soil Moisture:** Higher soil moisture levels (above 35%) were consistently associated with landslide alerts. This suggests that saturated soil can lead to increased instability, warranting alerts.
- **Tilt Angle:** An increase in tilt angle measurements, particularly above 15 degrees, was observed before landslides occurred, indicating that slope steepness plays a crucial role in landslide risk.
- **Vibration Levels:** The vibration sensor detected minimal activity during non-alert days, while increased vibration levels corresponded with landslide events, further validating the sensor's role in detecting ground movement.

Results :

The results from the experimental study are presented in the following table, highlighting key data points collected over a specified period:

SL No	Soil Moisture (%)	Tilt Angle (degrees)	Vibration Level (m/s²)	Landslide Alert (Yes/No)
1	15	8	0.02	No
2	22	12	0.03	No
3	35	14	0.05	Yes
4	42	18	0.06	Yes
5	50	22	0.07	Yes
6	28	10	0.02	No

Experimental Setup for Flood Module

The experimental setup for the IoT-based real-time flood monitoring system utilizes a NodeMCU microcontroller to collect and analyze data from various sensors deployed in flood-prone areas. The sensors used in this study include:

- **Water Level Sensor:** Measures the height of water within 1 meter of the system. A water level above 1 meter is considered critical for potential flooding.
- **Rainfall Sensor:** Detects rainfall intensity, with lower values indicating no rain and higher values indicating severe rain, which can lead to flooding.
- **Temperature Sensor:** Measures ambient temperature. Low temperatures can correlate with higher humidity levels, which may contribute to flooding conditions.
- **Humidity Sensor:** Monitors humidity levels, where high humidity paired with low temperature can increase the risk of flooding.

The NodeMCU is connected to these sensors, transmitting data to a cloud platform (e.g., ThingSpeak or AWS IoT) for real-time processing and analysis. This setup enables continuous monitoring of environmental conditions contributing to flooding, allowing timely alerts to be sent to users.

4.4 Results

The results from the experimental study are summarized in the following table, highlighting key data points collected over a specified monitoring period:

SL No	Water Level (cm)	Rainfall (mm)	Temperature (°C)	Humidity (%)	Flood Alert (Yes/No)
1	50	0	25	60	No
2	80	5	24	70	No
3	100	10	22	80	Yes
4	120	20	20	85	Yes
5	110	35	18	90	Yes
6	70	3	26	65	No

4.5 Results and Discussion

The data collected over the monitoring period indicates a clear correlation between water levels, rainfall, temperature, and humidity with the occurrence of flood alerts. For instance:

- **Water Level:** Water levels above 100 cm consistently correlated with flood alerts. This suggests that when water is within 1 meter of the system, it poses a significant risk of flooding.
- **Rainfall:** Higher rainfall measurements (above 10 mm) were observed before triggering flood alerts, indicating that severe rain conditions contribute significantly to the risk of flooding.
- **Temperature and Humidity:** Low temperature readings (below 20°C) combined with high humidity levels (above 80%) were associated with flood alerts, suggesting that these conditions can increase the likelihood of flooding by promoting water saturation in the environment.

4.6 Comparison of Results

When comparing the results of this IoT-based landslide detection system with traditional methods, several key differences emerge:

1. **Real-time Monitoring:** The IoT system allows for continuous monitoring of conditions, whereas traditional methods often rely on periodic checks.
2. **Predictive Capability:** By analyzing historical data, the IoT system can provide predictive alerts based on environmental changes, reducing false alarms.
3. **Cost-effectiveness:** Utilizing low-cost sensors and the NodeMCU makes this system affordable for disaster-prone communities, contrasting with expensive traditional monitoring systems.

5. Conclusion and Future Scope

Conclusion

The IoT-Based Real-Time Flood and Landslide Detection and Monitoring System presents a significant advancement in disaster management technologies, specifically tailored to address the urgent need for timely and accurate detection of flood and landslides. By integrating low-cost sensors with a NodeMCU microcontroller, this system effectively monitors critical environmental factors, such as soil moisture, tilt angles, ground vibrations for landslide detection and ultrasonic sensor, rainfall sensor, humidity and temperature sensor for rainfall detection. The experimental results indicate a strong correlation between these monitored parameters and the likelihood of landslides, allowing for proactive alerts to mitigate potential risks.

The system's design emphasizes real-time data collection and analysis, enabling rapid responses to changing conditions. Furthermore, the use of cloud platforms for data visualization enhances community engagement by providing residents with essential information regarding their safety. This project not only contributes to the field of environmental monitoring but also emphasizes the importance of utilizing accessible technology to empower vulnerable communities in disaster-prone areas.

Future Scope

While the current system demonstrates promising results, several avenues for future development can further enhance its effectiveness:

1. **Integration of Additional Sensors:**

- Future iterations could incorporate additional sensors, such as rainfall and temperature sensors, to provide a more comprehensive understanding of the environmental conditions contributing to landslides.

2. **Machine Learning Enhancements:**
    - Implementing advanced machine learning algorithms can improve predictive analytics capabilities, allowing the system to learn from historical data and adapt to new patterns of landslide activity over time..
3. **Long-Term Monitoring and Data Analysis:**
    - Continuous long-term monitoring of the area can provide valuable insights into the trends and patterns of landslide occurrences, allowing for more refined risk assessments and improved response strategies.
4. **Collaboration with Local Authorities:**
    - Partnering with local government and disaster management agencies can enhance the system's impact, ensuring that alerts are disseminated effectively and that communities receive the necessary support during emergencies.
5. **Scalability:**
    - The design can be adapted to monitor various geographic locations, making it scalable for different regions facing similar risks. This scalability can provide a wider reach for the technology, benefiting more communities.

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7.Video Presentation link:

https://youtu.be/d3HR1fuNPLs