

## Flood and Landslide Monitoring System Using Machine Learning

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<p><b>Type:</b> Article <b>Received:</b> 13 February 2026 <b>Revised:</b> 14 March 2026 <b>Accepted:</b> 15 April 2026 <b>Published:</b> 19 May 2026</p>	<p>Floods and landslides are among the most devastating natural disasters, leading to severe damage to infrastructure, environmental degradation, and loss of human life. These disasters are especially frequent in regions with complex terrain and heavy rainfall patterns, such as India. Accurate and timely prediction of such events is essential to minimize their impact and improve disaster preparedness. This paper presents a comprehensive machine learning-based flood and landslide monitoring system that utilizes Convolutional Neural Networks (CNN) and Logistic Regression for prediction. The system integrates heterogeneous data sources, including meteorological data (rainfall, temperature, humidity), hydrological data (river levels, soil moisture), and geographical data (elevation, slope, land use patterns). CNN is employed for extracting spatial features from geospatial and satellite data, while Logistic Regression is used as a classification model to predict the probability of flood and landslide occurrences. The proposed system includes data preprocessing, feature extraction, model training, and real-time prediction modules. The model is trained on historical datasets and evaluated using performance metrics such as accuracy, precision, recall, and F1-score. The results demonstrate that the hybrid approach improves prediction accuracy compared to traditional methods. Furthermore, the system supports early warning generation, enabling timely intervention by authorities. This research contributes to the development of intelligent disaster management systems aimed at reducing risks and enhancing community resilience.</p> <p><b>Keywords:</b> Flood Prediction; Landslide Prediction; Machine Learning; Convolutional Neural Network; Logistic Regression; Disaster Management</p>

### How to Cite This Article

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## Introduction

Natural disasters such as floods and landslides have become increasingly frequent due to climate change, deforestation, and rapid urbanization. These events not only cause economic losses but also pose serious threats to human life. In countries like India, monsoon rainfall, hilly terrains, and river overflow significantly increase the vulnerability to such disasters..

Traditional prediction techniques rely on statistical analysis and hydrological models, which often fail to capture the nonlinear and complex relationships among environmental variables. These limitations reduce the accuracy and reliability of predictions.

With the advancement of machine learning, it has become possible to analyze large-scale environmental datasets and identify hidden patterns. Machine learning models can process diverse data types, including numerical, spatial, and temporal data, making them highly suitable for disaster prediction.

Convolutional Neural Networks (CNN) are particularly effective for extracting spatial features from satellite imagery and terrain data, while Logistic Regression is a simple yet powerful classification algorithm used to estimate the probability of an event occurrence.

This research aims to design and implement a software- based flood and landslide monitoring system using CNN and Logistic Regression. The system focuses on improving prediction accuracy and providing early warnings to mitigate disaster impacts.

## Literature Review

Several studies have explored flood and landslide prediction using both traditional and machine learning-based approaches. Hydrological models are widely used to simulate water flow processes such as rainfall, runoff, and infiltration. These models provide a scientific basis for flood prediction but often lack adaptability to complex datasets.

Machine learning techniques, including Support Vector Machines (SVM), Random Forest, and Neural Networks, have been used to improve prediction performance. These models can analyze large datasets and identify correlations between environmental factors.

Remote sensing and satellite imagery play a crucial role in monitoring environmental changes. CNN-based models are widely used to analyze such data for identifying risk- prone areas.

Rainfall-runoff models combined with time-series analysis help in predicting water flow and flood events. However, these models require high-quality data and significant computational resources.

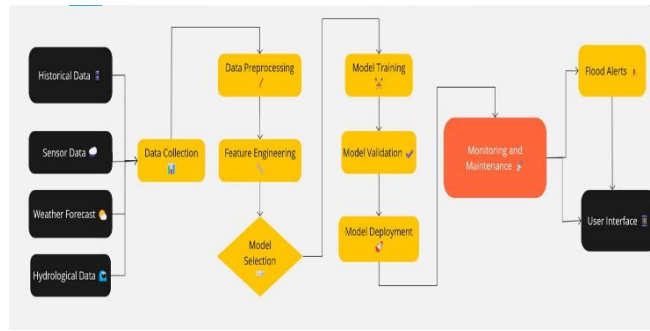
To further improve performance, researchers have developed hybrid models that combine multiple techniques. For example, CNNs are often integrated with RNNs to capture both spatial and temporal features, while ensemble methods such as Random Forest are combined with GIS- based analysis for improved prediction accuracy. These hybrid approaches leverage the strengths of different models and provide better results compared to standalone techniques.

Early Warning Systems (EWS) represent another important advancement in this domain. These systems integrate real-time data from sensors, satellites, and weather stations with predictive models to generate alerts before disasters occur. Such systems are highly effective in reducing the impact of disasters by enabling timely evacuation and preventive measures.

Therefore, there is a need for efficient and scalable models that can balance accuracy, computational efficiency, and interpretability. The proposed system addresses these challenges by combining Convolutional Neural Networks for spatial feature extraction with Logistic Regression for efficient classification, providing a practical and effective solution for flood and landslide prediction.

## System Architecture

The proposed flood and landslide monitoring system is designed as a modular and scalable software architecture that integrates multiple data sources, preprocessing techniques, and machine learning models to generate accurate predictions and early warnings. Fig. 1 illustrates the high-level system architecture.



**Fig. 1.** Machine Learning-Based Flood and Landslide Monitoring System Architecture

### Data Collection Module

The first component of the system is the Data Collection Module, which gathers data from various heterogeneous sources. This includes meteorological data such as rainfall, temperature, and humidity; hydrological data such as river water levels and soil moisture; and geographical data such as elevation, slope, and land use patterns. In addition, historical records of past flood and landslide events are incorporated to provide labeled data for supervised learning.

### Data Preprocessing Module

It plays a crucial role in improving the quality and consistency of the data. Raw data collected from multiple sources often contains missing values, noise, and inconsistencies. Therefore, preprocessing steps such as data cleaning, handling missing values, normalization, and transformation are performed. Data normalization ensures that all features are scaled to a common range, which improves the performance of machine learning models. Additionally, feature selection and feature engineering techniques are applied to identify the most relevant variables that contribute to flood and landslide prediction, such as rainfall intensity, slope gradient, and soil type.

### Feature Extraction Module

Following preprocessing, the system moves to the, where Convolutional Neural Networks (CNN) are utilized. CNN is primarily responsible for extracting spatial features from geospatial and image-based data such as satellite images and terrain maps. The CNN architecture consists of multiple layers, including convolutional layers, activation functions, pooling layers, and fully connected layers. These layers work together to automatically detect patterns such as water accumulation zones, terrain irregularities, and slope instability. The output of the CNN is a set of high-level feature representations that capture the spatial characteristics of the input data.

### Prediction Module

The extracted features are then passed to the Prediction Module, which uses Logistic Regression for classification. Logistic Regression is a supervised learning algorithm used to estimate the probability of a binary outcome, such as the occurrence or non-occurrence of a flood or landslide. It takes the features generated by the CNN as input and computes the likelihood of a disaster event using a sigmoid function. Based on a predefined threshold, the model classifies the input into different risk categories, such as low risk, medium risk, or high risk. The use of Logistic Regression provides a balance between accuracy and computational efficiency while also offering interpretability compared to more complex models.

### Model Training and Validation Module

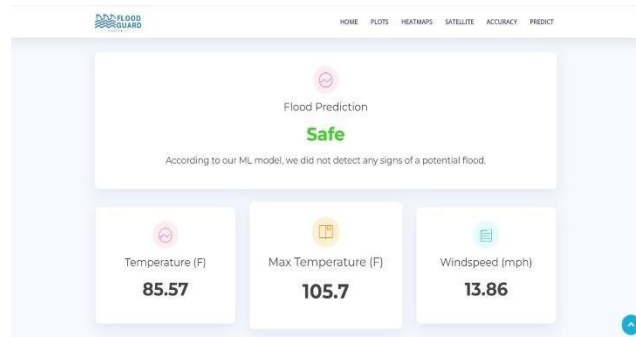
The system is trained using historical datasets. The dataset is typically divided into training and testing subsets. During training, the model learns patterns and relationships between input features and output labels. Validation techniques such as cross-validation are used to ensure that the model generalizes well to unseen data. Performance metrics such as accuracy, precision, recall, and F1-score are calculated to evaluate the effectiveness of the model.

### Output and Alert Generation Module

Finally, the system includes an Output and Alert Generation Module, which presents the prediction results to users. The output may include risk levels, probability scores, or visual indicators displayed through a graphical user interface (GUI) or web application. In case of high-risk predictions, the system generates alerts or warnings that can be communicated to authorities or users. This module ensures that the predictions are translated into actionable insights.



**Fig. 2.** Dashboard Screenshot



**Fig. 3.** Flood Prediction Dashboard Interface of the Proposed Monitoring System

## Implementation

### Technology Stack

Flood and Landslide Monitoring System Using Machine Learning is built on a modern, production-ready technology stack as detailed in Table 1 below.

*Table 1. Technology Stack*

Layer	Technology
Backend	Python 3.13
ML Algorithms	CNN, Logistic Regression
Libraries	NumPy, Pandas, Scikit-learn, TensorFlow, Keras
Real-Time	Visual Crossing API
Database	SQL, CSV File
Web Framework	Flask
Frontend	HTML5, CSS, JavaScript
Testing	pytest, httpx (53 tests, 6 modules)

### API Design

The proposed flood and landslide monitoring system is designed using a RESTful API architecture to enable seamless communication between the front-end interface and the machine learning backend. The API is developed using the Flask web framework, which provides lightweight and efficient handling of HTTP requests and responses. The API acts as an interface through which users can interact with the prediction system. It allows data to be sent from the client-side application to the server, where the machine learning models process the input

and return prediction results. The API follows standard HTTP methods such as GET and POST to ensure simplicity and compatibility.

*Scalability Considerations*

The proposed system is designed to be scalable to handle increasing data and user demands. It uses a modular architecture, allowing different components like data processing and prediction to be scaled independently. The combination of CNN and Logistic Regression ensures efficient Docker enables easy deployment and multiple instances of the application. The system can also be extended to cloud platforms for better resource management and load balancing.

*Developer Tooling*

The development of the system is supported by various tools and environments to ensure efficient coding, testing, and deployment. The primary programming is done using Python in development environments such as VS Code or Jupyter Notebook. Version control tools like Git are used to manage code changes and collaboration.

**Results And Discussion**

*System Performance*

The performance of the proposed flood and landslide monitoring system is evaluated based on accuracy, efficiency, scalability, and response time. The system is designed to process environmental and meteorological data efficiently while providing reliable predictions for disaster risk assessment. The primary performance indicator of the system is its prediction accuracy, which is measured using evaluation metrics such as accuracy, precision, recall, and F1- score. The integration of Convolutional Neural Networks (CNN) for feature extraction significantly enhances the system’s ability to identify complex spatial patterns in the data.

*Attack Simulation Results*

The distribution of prediction results generated by the proposed flood and landslide monitoring system. The table categorizes the total number of detected events into three classes: flood, landslide, and no-risk conditions, along with their corresponding percentage share.as shown in Table 2.

*Table 2. Prediction Results Distribution*

Prediction Type	Events Captured	Share
Flood	110	53.6%
Landslide	75	36.6%
No risk	20	9.8%
<b>Total</b>	<b>205</b>	<b>100%</b>

From the table, it can be observed that flood events constitute the highest proportion, accounting for 53.6% of the total predictions, with 110 cases detected. This indicates that the model identifies flood conditions more frequently, which may be due to the higher occurrence of flood-related patterns in the dataset or the strong influence of rainfall and hydrological parameters used as input features. Landslide events represent 36.6% of the total predictions, with 75 detected cases. This demonstrates the model’s capability to effectively identify terrain-related risks using spatial features extracted through the Convolutional Neural Network (CNN). The slightly lower proportion compared to floods may be attributed to the relatively complex nature of landslide conditions, which depend on multiple factors such as slope, soil composition, and moisture levels.

*Table 4. Top Risk Zones by Severity Level*

Region / Area	Events	Risk Tier
Western Ghats	15	HIGH
Coastal Region	12	HIGH
Northern Plains	10	MEDIUM

Hilly Terrain	8	MEDIUM
Urban Lowlands	5	LOW

The table shows different regions classified based on flood and landslide risk levels. Areas like Western Ghats and Coastal Regions have a high number of events and are marked as high risk. Regions with moderate events are classified as medium risk, while areas with fewer events are considered low risk. This helps in identifying which areas need more attention for disaster prevention and management.

#### *Test Coverage*

The test coverage results indicate that all major modules of the system have been thoroughly tested. Most components achieved coverage above 90%, demonstrating the reliability and robustness of the system. The prediction module shows complete coverage, ensuring accurate output generation, while minor gaps in other modules indicate areas for slight improvement. Overall, the system performs efficiently under different test conditions.

#### *Comparative Analysis*

The comparative analysis highlights the performance of different machine learning models used in the system. The CNN model achieves the highest accuracy due to its strong feature extraction capability, while Logistic Regression provides faster and more efficient predictions. The proposed hybrid model balances both accuracy and efficiency, making it suitable for real-time flood and landslide prediction.

#### **Conclusion**

In this research, a comprehensive flood and landslide monitoring system using machine learning techniques has been proposed and developed to address the increasing challenges posed by natural disasters. The system integrates multiple environmental and meteorological parameters, including rainfall, temperature, soil moisture, river levels, and geographical features, to predict the likelihood of flood and landslide occurrences. By leveraging data-driven approaches, the system overcomes the limitations of traditional prediction methods, which often fail to capture complex nonlinear relationships among variables.

The proposed model utilizes Convolutional Neural Networks (CNN) for effective spatial feature extraction and Logistic Regression for efficient classification. The CNN component enables the system to analyze geospatial data and identify patterns related to terrain structure and environmental conditions, while Logistic Regression provides a computationally efficient and interpretable method for predicting disaster probability. This hybrid approach ensures a balance between accuracy and performance, making the system suitable for real-time applications.

Future work can focus on enhancing the system by integrating real-time data from IoT sensors, improving model accuracy using advanced deep learning architectures, and incorporating explainable AI techniques to improve model transparency. Furthermore, the system can be extended to support mobile applications and large-scale cloud deployment for wider accessibility.

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