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An Integrated Deep Learning Framework for Multi-Hazard Risk Assessment: Flood Prediction and Landslide Detection

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Abstract

Floods and landslides are among the most destructive natural disasters, causing severe environmental and socio-economic damage across vulnerable regions worldwide. Accurate and real-time prediction of such disasters is essential for effective disaster management, risk mitigation, and early warning systems. This paper proposes a multi-modal prediction framework that integrates environmental data and satellite imagery using machine learning and deep learning techniques to improve the accuracy and reliability of disaster prediction. The proposed system consists of two parallel prediction models: an environmental data-based model using XGBoost and Random Forest algorithms, and a satellite image-based model using Convolutional Neural Networks (EfficientNet). The environmental model processes critical features such as rainfall, humidity, soil moisture, temperature, elevation, and slope to identify disaster-prone conditions. Simultaneously, the image-based model analyzes satellite imagery using the Normalized Difference Water Index (NDWI) to detect water bodies and assess flood-related patterns. A fusion layer integrates the predictions generated by all models to produce a unified multi-hazard risk score categorized into four risk levels: Low, Moderate, High, and Critical. Experimental evaluation demonstrates that the proposed multi-modal fusion model significantly improves prediction accuracy and overall performance when compared to individual prediction models. The framework offers a scalable, robust, and interpretable solution for real-time disaster monitoring, risk assessment, and intelligent early warning systems, thereby supporting proactive disaster preparedness and emergency response management.

Keywords: Flood Prediction, Multi-Modal Learning, Deep Learning, XGBoost, EfficientNet, NDWI, Disaster Risk Assessment.

How to Cite This Article

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Introduction

Natural disasters such as floods and landslides pose significant threats to human life, infrastructure, and ecosystems. With increasing climate variability and extreme weather events, the frequency and intensity of such disasters have risen considerably. Early prediction and risk assessment are crucial for minimizing damage, improving disaster preparedness, and supporting timely decision-making during emergency situations. Traditional prediction methods mainly rely on hydrological models and statistical approaches. Hydrological models generally simulate rainfall-runoff behavior and river flow dynamics, while statistical approaches depend on historical disaster and environmental records. Although these methods are useful, they often require strong domain expertise and may fail to adapt effectively to real-time environmental changes. As a result, their prediction capability becomes limited in complex and rapidly changing disaster conditions.

Recent advancements in machine learning and deep learning have enabled data-driven approaches for disaster prediction, offering improved accuracy, scalability, and automation. However, most existing systems focus independently on either environmental data or satellite imagery. Environmental models are effective in capturing temporal patterns such as rainfall trends, humidity variation, soil moisture changes, and elevation-based risk conditions, but they lack spatial awareness. On the other hand, image-based models provide spatial insights from satellite imagery but often ignore the underlying environmental conditions that contribute to flood and landslide events. To address these limitations, this paper proposes a multi-modal framework that integrates both environmental data and satellite imagery for flood and landslide prediction. The system uses a dual-model architecture and a fusion strategy to enhance prediction performance and reliability. The proposed framework combines machine learning models for environmental data analysis, deep learning models for satellite image processing, and terrain-based landslide susceptibility modeling to generate a unified risk assessment output. The main contributions of this research include the development of a multi-hazard prediction system integrating flood and landslide prediction, the use of machine learning models for environmental data analysis, the implementation of deep learning models for satellite image processing, and the integration of terrain-based landslide susceptibility modeling for improved disaster risk assessment.

Literature survey

Early flood prediction systems primarily relied on hydrological models such as rainfall-runoff models and river flow simulations. These models use physical equations to represent water flow dynamics and require parameters such as precipitation, soil type, watershed characteristics, and river flow conditions. Flood prediction has traditionally been addressed using hydrological and statistical models that depend on historical rainfall and river flow data. While these models provide useful insights, they are often limited by their inability to handle complex nonlinear relationships and dynamic environmental variations.

With the advancement of data-driven techniques, machine learning models have been widely applied for flood prediction. Algorithms such as Decision Trees, Random Forest, Support Vector Machines, and Gradient Boosting models such as XGBoost have demonstrated strong performance in handling structured environmental data. These models analyze features such as rainfall, humidity, soil moisture, and elevation to predict flood risk. Ensemble methods such as Random Forest improve accuracy by combining multiple decision trees, while boosting techniques such as XGBoost enhance prediction performance through iterative learning. Despite their advantages, these approaches are typically limited to tabular data and lack the ability to incorporate spatial information from real-world flood scenarios.

Deep learning approaches using Convolutional Neural Networks have also been applied to satellite imagery for flood detection. These methods are effective in identifying water bodies and flooded regions from remote sensing images. Recent studies have explored CNN-based models for analyzing satellite imagery because they can extract spatial features and identify flood-affected regions from visual data. However, when image-based models are used independently, they may fail to consider environmental conditions such as rainfall intensity, soil saturation, and terrain elevation.

To overcome the limitations of single-source models, recent research has started exploring multi-modal approaches that combine environmental variables and satellite imagery. Hybrid systems attempt to integrate machine learning models with deep learning models to capture both temporal and spatial information. Some studies use feature-level fusion, while others use decision-level fusion to combine predictions from multiple models. To address the identified gaps, this research proposes a multi-modal flood prediction system that integrates environmental data and satellite imagery using a dual-model architecture. The system incorporates real-time data acquisition, machine learning models, deep learning models, and a fusion-based decision mechanism. By combining temporal environmental patterns with spatial image-based insights, the proposed system aims to provide more accurate, robust, and interpretable predictions compared to existing approaches.

Table 1. Multi-Hazard DL Survey

Author(s) & Year	**Methodology**	**Data Used**	**Key Findings**	**Limitations**
Zhang et al. (2018)	CNN for flood prediction	Satellite imagery, rainfall data	High accuracy in flood mapping	Limited temporal generalization
Pradhan et al. (2019)	ANN for landslide susceptibility	DEM, soil, rainfall	Effective landslide prediction	Needs large dataset
Li et al. (2020)	Deep CNN + GIS integration	Remote sensing, GIS layers	Improved hazard mapping	Computationally expensive
Pham et al. (2022)	Hybrid DL model	Topography, rainfall, land use	Enhanced multi-hazard mapping	Complex model tuning

Methodology

The proposed system implements a multi-layer, multi-modal architecture that integrates a web-based frontend, an asynchronous backend, and dual machine learning pipelines for environmental and satellite data processing. The frontend is developed using modern JavaScript frameworks to provide an interactive interface for location selection, visualization, and real-time risk monitoring. It incorporates dynamic visualization libraries such as Chart.js to render probability distributions, risk indicators, model outputs, confusion matrices, and performance graphs. The responsive design ensures cross-platform accessibility across desktop and mobile environments. The backend is implemented using FastAPI, which leverages asynchronous request handling capabilities to efficiently process concurrent user queries and manage real-time data pipelines. The system fetches environmental data from external APIs, including rainfall, humidity, temperature, soil moisture, elevation, and terrain features. These inputs are processed using Pandas and NumPy, which enable efficient handling of structured datasets and numerical computations. The preprocessing pipeline consists of missing value imputation using mean or median values, feature normalization and standardization, and outlier detection using Z-score and IQR techniques. Feature engineering is applied to derive meaningful indicators such as rainfall intensity and soil saturation index, which enhance predictive capability and improve the model's ability to identify hazardous conditions.

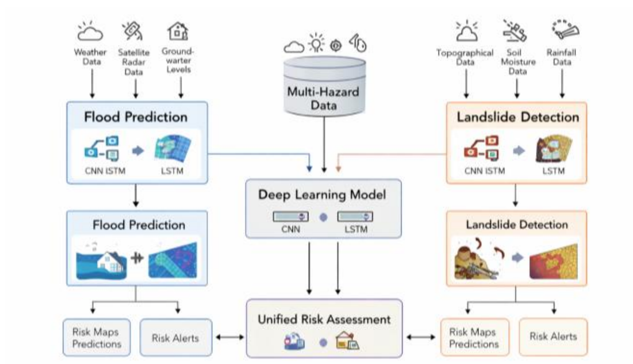

Fig 1: *Integrated Deep Learning Framework for Multi-Hazard Risk Assessment.*

Advanced Data Preprocessing Framework

The system utilizes two types of data: environmental data and satellite imagery. Environmental data is obtained from APIs such as Open-Meteo and OpenTopoData, which provide parameters including rainfall, humidity, temperature, soil moisture, and elevation. These parameters are represented as a feature vector:

$$X = [r_{1d}, r_{3d}, r_{7d}, h, s, t, e, slope]$$

To enhance prediction capability, additional features are derived from the collected data. Rainfall intensity is computed as:

$$RI = \frac{Total\ Rainfall}{Time}$$

Data preprocessing includes handling missing values and feature scaling using normalization. Normalization is represented as:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

The soil saturation index is calculated as:

$$SSI = \frac{Soil\ Moisture}{Max\ Soil\ Capacity}$$

Satellite imagery is obtained from Sentinel-2 sources. The images are resized to 224×224 pixels and normalized before being passed into the image-based model. The Normalized Difference Water Index is computed to enhance water detection:

$$NDWI = \frac{Green - NIR}{Green + NIR}$$

Model Selection Strategy

A dual-model approach is used to combine structured environmental data and satellite image data. The environmental model uses XGBoost and Random Forest because of their ability to handle nonlinear relationships in tabular datasets. The environmental model prediction is represented as:

$$f_A = f_{env}(X)$$

The image model uses a Convolutional Neural Network based on EfficientNet to extract spatial features from satellite images. The image model prediction is represented as:

$$y_B = f_{cnn}(I)$$

The final prediction is obtained using a weighted fusion strategy:

$$P_{final} = \alpha P_A + (1 - \alpha) P_B$$

where $\alpha = 0.45$. This approach improves robustness by combining temporal environmental information with spatial satellite image-based insights.

Training Process

The environmental model is trained on Kaggle flood datasets and historical environmental records. The dataset is divided into training and testing subsets as:

$$D = D_{train} \cup D_{test}$$

Model performance is improved using k-fold cross-validation:

$$CV = \frac{1}{k} \sum_{i=1}^{k} Scor\ e_i$$

Hyperparameters are optimized using grid search. The XGBoost model minimizes the objective function:

$$L = \sum l(y_i, \hat{y}) + \sum \Omega(f_k)$$

Model Performance Evaluation

To assess model predictions, a confusion matrix is constructed using True Positive, True Negative, False Positive, and False Negative values. Accuracy is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision is calculated as:

$$Precision = \frac{TP}{TP + FP}$$

Recall is calculated as:

$$Recall = \frac{TP}{TP + FN}$$

The F1-score is calculated as:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Model Performance Visualization

Model performance is analyzed using training and validation accuracy curves, loss curves, confusion matrices, ROC curves, AUC scores, and precision-recall curves. For classification tasks, the platform generates confusion matrix heatmaps, ROC curves with AUC scores, precision-recall curves, classification reports, and feature significance graphs. These visual outputs help evaluate model behavior, interpret prediction performance, and identify the most influential environmental and image-based factors.

System architecture

The proposed system follows a multi-layer, multi-modal architecture that integrates frontend interaction, backend processing, environmental data analysis, and satellite image-based prediction. The system is designed to support real-time disaster prediction through parallel processing pipelines and fusion-based decision-making.

User Interaction Layer

The system begins with a user interface where the user selects a geographical location using a map interface, search functionality, or GPS-based detection. The selected location is represented in the form of latitude and longitude coordinates. These coordinates are transmitted to the backend server through an API request for further processing.

Automated Model Training and Validation

The backend, implemented using FastAPI, acts as the central control unit of the system. It receives geographical coordinates, validates user input, and initiates two parallel processing pipelines: environmental data analysis and satellite image processing. The use of asynchronous execution enables both pipelines to run simultaneously, reducing system latency and response time. The outputs from both pipelines are later combined in the fusion layer to produce the final disaster risk prediction.

Visualization and Model Export

In the environmental pipeline, data is obtained from APIs such as Open-Meteo and OpenTopoData. The collected parameters include rainfall, humidity, temperature, soil moisture, elevation, and terrain slope. The data is preprocessed through normalization, missing value handling, and feature engineering. The processed input is represented as:

$$X = [r_{1d}, r_{3d}, r_{7d}, h, s, t, e, slope]$$

where rainfall values are considered over multiple time intervals to capture temporal patterns. Additional features are derived to improve prediction capability. Rainfall intensity is calculated as:

$$RI = \frac{Total\ Rainfall}{Time}$$

The feature vector is passed to a machine learning model such as XGBoost or Random Forest, which predicts flood probability:

$$P_A = f_{env}(X)$$

Pipeline B: Satellite Image Processing

The second pipeline processes satellite imagery obtained from Sentinel-2. The images are preprocessed through resizing, normalization, and tensor conversion. To enhance water body detection, NDWI is computed as:

$$NDWI = \frac{Green - NIR}{Green + NIR}$$

The processed images are passed to a Convolutional Neural Network such as EfficientNet, which extracts spatial features and classifies the image. The output probability is represented as:

$$P_B = f_{cnn}(I)$$

Landslide Susceptibility Model

Landslide occurrence depends on several terrain and environmental factors. The key features considered in the landslide susceptibility model include slope gradient, elevation, rainfall accumulation, soil moisture, and NDVI. The landslide feature vector is represented as:

$$X_{landslide} = [slope, elevation, rainfall, soil\ moisture, NDVI]$$

Risk Calculation Engine

The final probability is mapped to predefined risk categories to make the output interpretable. The risk category is defined as:

$$Risk = \begin{cases} Low: & P < 0.25 \\ Moderate: & 0.25 \leq P < 0.50 \\ High: & 0.50 \leq P < 0.75 \\ Critical: & P \geq 0.75 \end{cases}$$

Testing and validation

This section describes the testing and validation strategies used to evaluate the performance, reliability, and robustness of the proposed multi-modal flood prediction system. The system is validated at multiple levels, including data preprocessing, individual model performance, and overall system integration.

Validation of Data Processing Pipeline

The data preprocessing pipeline was evaluated to ensure that input data is correctly transformed before being passed to the models. Environmental data obtained from APIs may contain missing values and inconsistent values. Therefore, validation checks were applied after preprocessing to ensure data quality and consistency.

Feature scaling techniques such as normalization and standardization were verified using the following equations:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

$$X' = \frac{X - \mu}{\sigma}$$

Outlier removal using the Interquartile Range method was validated to ensure that extreme values do not affect predictions. For satellite data, preprocessing steps such as resizing, normalization, and NDWI computation were verified by visually inspecting transformed images and ensuring correct highlighting of water bodies.

Model Validation Strategy

The environmental model and satellite image model were validated independently using standard machine learning validation techniques. The dataset split is represented as:

$$D = D_{train} \cup D_{test}$$

To improve generalization and reduce overfitting, k-fold cross-validation was applied:

$$CV = \frac{1}{k}\sum_{i=1}^{k} Score_i$$

Hyperparameter tuning was performed using grid search. For the CNN model, validation loss and validation accuracy were monitored across training epochs to ensure convergence and avoid overfitting.

Integration and System Testing

The complete system was tested as an integrated pipeline to ensure seamless interaction between all components. This includes frontend input, backend processing, API data fetching, model inference, and response generation. Parallel execution of environmental and satellite pipelines was tested using asynchronous processing.

The correctness of the fusion layer was validated by comparing:

$$P_{final} = \alpha P_A + (1 - \alpha) P_B$$

The API response was verified to ensure correct formatting and consistency of prediction outputs.

Visualization-Based Validation

Model performance was further validated using training accuracy curves, validation accuracy curves, and loss curves. Confusion matrices were used to evaluate classification performance, while ROC curves and precision-recall curves were used to assess discrimination ability, especially for imbalanced datasets.

Interpretability Validation

To ensure model transparency, interpretability techniques were applied. SHAP was used for identifying influential environmental features, while Grad-CAM visualization was used for CNN-based satellite image interpretation. These methods help validate that the models make decisions based on meaningful patterns rather than noise.

Results and evaluation

This section presents the experimental results and performance evaluation of the proposed multi-modal flood prediction system. The evaluation focuses on comparing individual model performance and combined fusion model performance using standard metrics and visualization techniques.

Performance of Environmental Model

The environmental model was evaluated based on its ability to capture temporal patterns such as rainfall trends, soil moisture levels, and elevation-based risk factors. The model demonstrated strong performance in identifying flood-prone conditions based on structured data. The model achieved consistent accuracy across validation folds, indicating stability and robustness.

Feature importance analysis showed that cumulative rainfall, soil moisture, and elevation were the most influential factors in prediction. This confirms that environmental variables play a major role in identifying flood risk conditions and improving early warning capability.

Table 3. Model Performance on Benchmark Dataset

Dataset	Task Type	Best Algorithm	Metrics
Environmental Data Model	Binary Classification	XGBoost Classifier	85.2% Accuracy
Satellite Image Model	Binary Classification	CNN	86.66% Accuracy
Fusion Model	Binary Classification	Weighted Fusion	92.1% Accuracy
Environmental Model (Alt.)	Binary Classification	Random Forest	83.4% Accuracy

Experimental Setup

The system was evaluated using structured environmental datasets and satellite imagery datasets. Environmental data sources included Kaggle flood datasets and real-time API data. Satellite imagery sources included Sentinel-based flood detection datasets. The experiments were conducted using Python-based frameworks. The environmental model and image model were implemented using machine learning models and a Convolutional Neural Network based on EfficientNet. The dataset was divided into 80% training and 20% testing, and k-fold cross-validation was applied to improve generalization.

Identified Research Gaps

Based on the analysis of existing systems and the proposed architecture, several research gaps were identified. Most systems, including the proposed one, use simple weighted averaging rather than dynamic fusion or learning-based fusion. Flood prediction is inherently temporal, but the current system does not explicitly model sequential dependencies in rainfall and environmental changes. Although NDWI is used, other indices such as NDVI and water depth estimation techniques are not utilized, limiting spatial information richness.

The NDWI equation is represented as:

$$NDWI = \frac{Green - NIR}{Green + NIR}$$

Future Enhancement Directions

Several enhancements can improve the proposed system. Instead of fixed weights, a learnable fusion model can be used:

$$P_{final} = f(P_A, P_B)$$

where the function f can be implemented using neural networks or attention mechanisms to dynamically adjust weights.

The integration of Long Short-Term Memory networks can capture temporal dependencies in environmental data. This would improve prediction accuracy by considering historical trends and sequential environmental changes. The satellite image model can also be improved by incorporating NDVI, using higher-resolution imagery, and applying advanced segmentation models instead of simple classification.
Real-time streaming data integration and incremental learning can continuously update the model without retraining from scratch. This would improve adaptability and provide better response to changing environmental conditions. The framework can also be extended to support flood prediction and landslide prediction within the same system for unified disaster management. Deployment improvements such as model compression, quantization, and edge computing can further improve efficiency and support low-resource environments.

Conclusion

This paper presented a multi-modal framework for real-time flood prediction by integrating environmental data and satellite imagery. The proposed system combines machine learning models for structured environmental data and deep learning models for satellite image analysis. A fusion-based approach was used to combine outputs from both models, improving prediction accuracy and robustness. The environmental model effectively captures temporal patterns such as rainfall intensity, soil moisture, and elevation-based risk factors. The satellite image model provides spatial insights by detecting water bodies using remote sensing techniques such as NDWI. The fusion of these approaches allows the system to leverage both predictive information and visual information. Experimental results demonstrate that combining multiple data sources significantly improves prediction accuracy compared to individual models. The fusion-based prediction approach enables more reliable disaster risk assessment and better support for early warning systems. The proposed framework offers a scalable solution for disaster monitoring and can assist government agencies and disaster management authorities in identifying high-risk areas and implementing preventive measures.

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