
PROACTIVE DISASTER MANAGEMENT THROUGH AI-DRIVEN GEOSPATIAL PREDICTION AND SATELLITE ANALYTICS

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Article Received: 16 February 2026, Article Revised: 06 March 2026, Published on: 26 March 2026

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DOI: <https://doi-doi.org/101555/ijarp.5977>

2. ABSTRACT

Natural and human-induced disasters such as floods, landslides, wildfires, earthquakes, and conflict-related land degradation are increasing in frequency and severity across the world, causing significant loss of human life, damage to infrastructure, and severe environmental impact. Traditional disaster management systems depend heavily on historical records and static geospatial data, limiting their ability to respond to rapidly evolving scenarios. Satellite image analysis using artificial intelligence (AI) can detect disasters but typically operates reactively, after events have occurred. To address these limitations, this study proposes an AI-based hybrid disaster management framework that integrates geospatial prediction models with real-time satellite image analysis to support proactive and intelligent disaster response. The proposed system employs machine learning algorithms including Random Forest and XGBoost for risk-level prediction using geospatial and climate data, and deep learning models (CNN/U-Net) for satellite image analysis and change detection. A data fusion and decision layer integrates outputs from both modules to produce comprehensive disaster severity assessments and early warnings. The system is deployed using the Streamlit framework, enabling users to upload satellite images and geospatial data for interactive analysis. Upon analysis, the dashboard automatically generates a detailed AI-based disaster assessment report, improving transparency and usability. The framework aligns with Sustainable Development Goal SDG 3 (Good Health and Well-Being) by enabling timely disaster response and SDG 9 (Industry, Innovation and Infrastructure) by leveraging AI for scalable disaster management.

3. KEYWORDS: Disaster Management; Geospatial Prediction; Satellite Analytics; Deep Learning; Random Forest; Convolutional Neural Network; Early Warning System

4. INTRODUCTION

The healthcare and disaster management sectors have witnessed rapid advancements through the adoption of Artificial Intelligence (AI). Among various applications, proactive disaster prediction and real-time monitoring have gained significant importance. Natural disasters such as floods, landslides, wildfires, and earthquakes have severe global impact, often requiring immediate and well-coordinated response mechanisms. Traditional disaster management systems depend heavily on historical records and static geospatial data, which limits their ability to respond to rapidly changing situations.

Deep Learning, a subset of AI, has demonstrated remarkable performance in remote sensing and geospatial analysis tasks. In particular, Convolutional Neural Networks (CNNs) have excelled in image segmentation and damage detection. Machine learning models like Random Forest and XGBoost have proven effective in risk classification using multi-modal data. Recently, U-Net based architectures have emerged as powerful models for pixel-level disaster segmentation from satellite imagery.

Despite advancements in remote sensing and geospatial technology, existing disaster management systems face several key challenges. Prediction models lack real-time awareness, satellite-based detection systems are mostly reactive, and independent systems lead to fragmented and delayed emergency responses. There is a critical need for an integrated intelligent system that can automatically analyse geospatial data and satellite imagery to classify disaster risk with high accuracy.

This study proposes a hybrid AI framework that combines machine learning-based geospatial prediction with deep learning-based satellite image analysis. The objectives of this project are:

- To build a geospatial risk prediction model using historical disaster, climate, and terrain data.
- To design a satellite image analysis module using CNN/U-Net for disaster detection and damage mapping.
- To evaluate model performance using multiple metrics including confusion matrix, ROC curve, and classification reports.

- To generate risk maps and visualisations highlighting affected regions for decision support.
- To deploy the system as an interactive web application accessible to emergency responders and authorities.

5. MATERIALS AND METHODS

5.1 System Architecture

The proposed system follows a hybrid architecture comprising two primary computational modules: (i) a Machine Learning (ML) module for geospatial risk prediction, and (ii) a Deep Learning (DL) module for satellite image analysis. A Data Fusion and Decision Layer integrates the outputs of both modules to generate consolidated disaster severity assessments. The final results are presented through a Streamlit-based interactive web dashboard.

5.2 Dataset

The system utilises a curated dataset comprising Sentinel-2 and Landsat-8 satellite images across five disaster categories: Normal, Flood, Wildfire, Cyclone, and Earthquake. Geospatial climate data including rainfall, temperature, wind speed, humidity, and atmospheric pressure were sourced from publicly available meteorological repositories. For flood prediction, a dedicated flood probability dataset with 20 geospatial features was used. For cyclone prediction, the Australian weather dataset (weatherAUS.csv) was employed, and for wildfire prediction, the UCI Forest Fires dataset (forestfires.csv) was used.

5.3 Software and Tools

The system was implemented using Python as the core programming language. The following libraries and frameworks were used:

- TensorFlow / Keras: For deep learning model training and inference (CNN/U-Net).
- Scikit-learn / XGBoost: For machine learning-based risk prediction (Random Forest, XGBoost).
- Rasterio / GDAL: For reading and processing satellite image files in geospatial formats.
- OpenCV / NumPy: For image preprocessing, normalisation, and change detection.
- Streamlit: For building the interactive web-based dashboard.
- Matplotlib / Plotly: For generating risk maps, evaluation plots, and disaster visualisations.
- OpenWeatherMap API: For fetching real-time weather data by city name.

5.4 Data Preprocessing

Satellite images were resized to 224x224 pixels and normalised to the [0, 1] range. Cloud noise and missing data in satellite imagery were handled using masking techniques. Climate and terrain datasets were cleaned by removing outliers and imputing missing values. Spectral indices, namely NDVI (Normalised Difference Vegetation Index) and NDWI (Normalised Difference Water Index), were computed from satellite spectral bands. Terrain features including elevation, slope, and land-use classification were also extracted.

5.5 Machine Learning Module

Random Forest and XGBoost classifiers were trained to predict disaster risk levels (Low / Medium / High) based on extracted geospatial and climate feature vectors. For flood probability estimation, a Random Forest Regressor with 200 estimators was trained on 20 geospatial features. For cyclone prediction, a Random Forest Classifier was trained on temperature, rainfall, wind speed, humidity, and pressure. For wildfire risk, a classifier was trained using temperature, relative humidity, wind speed, and rainfall. All models were evaluated using accuracy score, Mean Absolute Error (MAE), and R² Score.

5.6 Deep Learning Module

A CNN architecture based on MobileNetV2 pretrained on ImageNet was fine-tuned for satellite image classification across four disaster classes (Cyclone, Fire, Flood, Normal). The base model was frozen to retain learned feature representations, and a Global Average Pooling layer followed by a Dropout (0.3) and a Dense softmax layer were added for classification. The model was trained for 10 epochs with a batch size of 32 using the Adam optimiser with sparse categorical cross-entropy loss. A U-Net architecture was used for pixel-level change detection and damage segmentation in pre- and post-disaster satellite image pairs.

5.7 Data Fusion and Decision Layer

The data fusion layer combines the ML risk score and the DL image classification confidence score using a weighted formula: Final Risk Score = (0.6 x Image Score) + (0.4 x Max Weather Risk Score). Alert thresholds were defined as follows: Final Risk \geq 70% triggers an Emergency alert; 40% to 70% triggers a Warning; below 40% is classified as Advisory. Upon crossing the Emergency threshold, automated email alerts are dispatched to registered authorities using SMTP.

5.8 Deployment

The complete system was deployed as a Streamlit web application accessible via a browser. Users can enter a city name to fetch real-time weather data, upload satellite images, and receive instant risk predictions, damage maps, alert levels, and downloadable disaster assessment reports. The application runs locally or can be hosted on cloud servers for wider accessibility.

5.9 Software Development Model

The Incremental Software Development Model was adopted for this project due to its suitability for parallel development of model, frontend, and backend components, and for enabling iterative refinement across development cycles. This model allowed for fast prototyping and validation of individual modules before integration.

6. RESULTS AND DISCUSSION

6.1 Results

The system was evaluated on a held-out test set. The CNN-based satellite image classifier achieved high classification accuracy across the four disaster categories (Cyclone, Fire, Flood, Normal), demonstrating the effectiveness of transfer learning with MobileNetV2. The Random Forest classifiers for cyclone and wildfire risk prediction, as well as the flood probability regressor, were validated using accuracy score and R^2 score respectively. Risk prediction outputs were presented as interactive bar charts via Plotly, and the overall disaster severity was displayed as a gauge indicator.

In a sample test using the city of Chennai, India, the system fetched real-time weather data (Temperature: 31.48°C, Humidity: 63%, Wind Speed: 4.63 m/s, Rainfall: 0 mm, Pressure: 1013 hPa) and returned the following risk estimates: Cyclone Risk = 0.00%, Flood Risk = 40.65%, Fire Risk = 100.00%. A concurrently uploaded cyclone satellite image was classified with 99.02% confidence. The fused Final Risk Score was 99.41%, triggering an automated HIGH RISK emergency alert via email to the registered authority.

The alert and dashboard screens confirmed end-to-end functionality: satellite image upload, weather-based ML predictions, deep learning image classification, data fusion, and automated alerting all operated seamlessly within the Streamlit interface.

6.2 DISCUSSION

The proposed hybrid framework addresses the key limitations identified in existing literature. Unlike purely historical or reactive systems, the integration of real-time weather data with satellite image analysis enables proactive risk assessment before disasters escalate. The data fusion layer effectively combines heterogeneous information sources, yielding more reliable and contextually rich disaster assessments than single-modality approaches.

The literature review supports these findings. Saleem et al. [1] demonstrated the effectiveness of hybrid AI-geospatial models for proactive disaster management. Krestenitis et al. [4] confirmed the feasibility of CNN-based automated damage assessment from satellite imagery. The attention-based CNN proposed by Yang et al. [3] outperformed standard CNNs by focusing on critical spatial regions, a property partially replicated here through transfer learning. Abid et al. [5] highlighted the importance of unified integrated platforms for disaster management, which is realised in this work through the Streamlit-based dashboard.

The inclusion of explainability through AI decision explanations (listing contributing weather factors alongside risk scores) aligns with the XAI principles advocated in recent literature, and enhances end-user trust. The automated email alerting mechanism further bridges the gap between prediction and real-world response.

Limitations include dependency on internet connectivity for real-time weather data, the absence of ground truth validation on field datasets, and the current scope being limited to four disaster categories. Future work should address these gaps through cloud-based APIs, extended datasets, and mobile deployment.

7. CONCLUSION

This study presents an efficient AI-based hybrid framework for proactive disaster management by integrating geospatial prediction models with real-time satellite image analysis. By combining Random Forest and XGBoost for risk prediction with CNN/U-Net for damage detection and segmentation, the system enhances disaster preparedness and response efficiency compared to conventional reactive methods. The Streamlit-based deployment ensures accessibility for emergency responders across varied resource environments. The system supports real-time prediction, early warning generation, damage assessment, and interactive visualisation. Future enhancements include mobile integration, cloud and IoT

support, Explainable AI (XAI) incorporation, expanded disaster type coverage, multilingual support, and voice-enabled assistance.

8. ACKNOWLEDGEMENTS

The authors express sincere gratitude to Ms. RM. Suganya, M.E., Assistant Professor, Department of Information Technology, K.L.N. College of Engineering, for her invaluable guidance and supervision throughout this work. The authors also thank Dr. P. Ganesh Kumar, Head of the Department of Information Technology, for providing necessary resources and encouragement. This project was carried out during January 2026 to April 2026 as part of the B.Tech Project Work (20IT8L1) at K.L.N. College of Engineering, an Autonomous Institution affiliated to Anna University, Chennai.

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