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Full Length Article

Ai-Driven Disaster Prediction And Intelligent Response System

Mrs. Tanveer Sultana[1], Areeba Alizah Fatima[2], Syeda Ayesha Tabassum[3], Hiba Tanheniyat[4]

[1]Associate Professor, Department Of Information Technology, Deccan College Of Engineering And Technology, Hyderabad, India

[2]Ug Students, Department Of Information Technology, Deccan College Of Engineering And Technology, Hyderabad, India

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Abstract

The increasing frequency and intensity of natural disasters such as floods, earthquakes, and cyclones necessitate the development of intelligent and proactive disaster management systems. This paper presents an AI-Driven Disaster Prediction and Intelligent Response System that integrates Machine Learning (ML), Large Language Models (LLMs), and Computer Vision techniques to enhance disaster prediction, situational awareness, and emergency response.

The proposed system leverages historical and environmental datasets to estimate disaster risks based on spatial and temporal inputs. Multiple ML models, including ensemble techniques, are utilized to improve prediction robustness, while real-time external data sources are incorporated to enhance contextual awareness. A Large Language Model is employed to interpret prediction outputs and generate human-readable insights along with safety recommendations.

To support emergency response, the system integrates a YOLO-based computer vision module for analyzing disaster images to detect affected individuals, infrastructure damage, and hazardous conditions. A conversational AI chatbot enables real-time interaction, while speech-to-text and text-to-speech modules provide voice-based accessibility. Additionally, a multilingual interface improves usability across diverse user groups.

The system further includes an interactive map-based visualization module for identifying disaster-prone regions and a cloud-based database for storing prediction history and user interactions. Experimental evaluation indicates effective disaster risk estimation and reliable object detection performance in simulated rescue scenarios. Overall, the proposed system offers a scalable and integrated framework for intelligent disaster management.

Index Terms*—Disaster Prediction, Intelligent Response System, Machine Learning (ML), Large Language Models (LLMs), Computer Vision, YOLO, Disaster Management, Real-Time Analytics, Risk Assessment, Emergency Response, Natural Language Processing (NLP), Speech-to-Text (STT), Text-to-Speech (TTS), Multimodal AI, Interactive Visualization, Deep Learning.*

I. **INTRODUCTION**

A. ***Background***

Natural disasters such as floods, earthquakes, and cyclones have increased significantly in frequency and intensity over recent decades, causing severe damage to human life, infrastructure, and the global economy. Effective disaster management requires timely prediction, accurate risk assessment, and rapid response mechanisms. However, traditional disaster management systems are largely reactive, relying on manual data collection, fragmented information sources, and delayed decision-making processes.

In many regions, especially developing countries, disaster-related information is scattered across multiple platforms such as meteorological reports, historical datasets, news sources, and satellite data. The lack of integration among these data sources limits the ability of authorities to generate timely and accurate insights. Additionally, existing systems often fail to provide real-time situational awareness and personalized guidance to both emergency responders and the general public.

Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Computer Vision have opened new possibilities for improving disaster prediction and response. ML models can analyze historical and environmental data to estimate disaster risks, while Computer Vision techniques enable automated analysis of disaster scenes for rescue operations. Furthermore, Large Language Models (LLMs) have demonstrated strong capabilities in understanding and generating human-like responses, making them suitable for intelligent decision-support systems.

This research proposes an AI-Driven Disaster Prediction and Intelligent Response System, a comprehensive platform that integrates ML-based prediction, real-time data analysis, and vision-based rescue support. The system utilizes multiple ML models to estimate disaster risks based on spatial and temporal inputs, while real-time external data sources enhance contextual awareness. A YOLO-based computer vision module analyzes disaster images to detect affected individuals, damaged infrastructure, and hazardous conditions. Additionally, a conversational AI chatbot provides real-time guidance, supported by voice-based interaction and multilingual capabilities for improved accessibility.

The proposed system also includes an interactive map-based visualization module for identifying disaster-prone regions and a cloud-based database for storing historical predictions and user interactions. By combining multiple AI technologies into a unified framework, the system aims to transform disaster management from a reactive process into a proactive, intelligent, and scalable solution.

*B. **Research Gap***

Despite significant advancements in disaster prediction and management systems, several limitations remain in existing approaches. Most current systems are designed to address isolated components of disaster management, such as prediction or monitoring, without providing an integrated framework that supports end-to-end decision-making and response planning. Many machine learning-based models rely heavily on historical datasets and lack the capability to incorporate real-time contextual information, which limits their effectiveness in dynamic disaster scenarios.

Furthermore, existing solutions often do not support multi-modal inputs, such as text, images, and voice, reducing their applicability in real-world emergency situations where diverse forms of information are critical. The use of computer vision techniques for real-time rescue analysis is still limited, leading to insufficient situational awareness during disaster events. In addition, there is minimal adoption of advanced Large Language Models for generating intelligent explanations, contextual insights, and user-interactive guidance.

Another significant limitation is the lack of user-centric design and accessibility features in existing systems. Many disaster management solutions do not provide multilingual support or intuitive interfaces, which restricts their usability for diverse populations, especially in high-risk and rural regions. Additionally, most systems fail to deliver real-time, actionable insights tailored to both the general public and emergency responders, limiting their effectiveness during critical situations.

Moreover, existing approaches often do not incorporate interactive visualization techniques, such as map-based representations, to provide clear situational awareness of disaster-prone regions and affected areas. The absence of integrated data storage and historical analysis further restricts the ability to track patterns, evaluate predictions, and improve system performance over time. These limitations result in fragmented systems that are not fully capable of addressing the complex and dynamic nature of disaster management.

Therefore, there exists a need for a comprehensive and integrated disaster management system that combines machine learning-based prediction, real-time data integration, computer vision-based rescue analysis, and intelligent response generation into a unified framework. Such a system should support multi-modal interaction, provide real-time decision support, and offer scalable and accessible solutions for both authorities and the general public

*C. **Research Objectives***

The primary objective of this research is to develop an intelligent, AI-driven disaster prediction and response system that enhances risk assessment, situational awareness, and real-time decision-making during disaster scenarios.

The key objectives of the proposed system are as follows:

• To develop a machine learning-based disaster prediction model that estimates risk levels using spatial and temporal inputs.

• To utilize multiple machine learning algorithms, including ensemble methods, to improve prediction accuracy and robustness.

• To integrate real-time external data sources for enhancing contextual awareness and dynamic risk analysis.

• To design a Large Language Model-based module for interpreting predictions and generating human-readable insights and safety recommendations.

• To implement a YOLO-based computer vision module for detecting affected individuals, infrastructure damage, and hazardous conditions from disaster images.

• To develop a conversational AI chatbot for real-time disaster-related queries and interactive guidance.

• To enable multi-modal input support, including text, image, and voice, for improved accessibility and usability.

• To provide multilingual support to ensure accessibility for diverse user populations.

• To design an interactive map-based visualization module for representing disaster-prone regions and risk levels.

• To implement a cloud-based database for storing prediction history, user interactions, and analytical insights.

*D. **Rationale Of The Study***

This research addresses a critical need for improving disaster preparedness, risk assessment, and emergency response through the use of advanced Artificial Intelligence technologies. With the increasing impact of natural disasters on human life and infrastructure, there is a growing demand for intelligent systems that can provide timely predictions and actionable insights.

By integrating Machine Learning, Large Language Models, and Computer Vision into a unified framework, the proposed system offers a comprehensive solution that goes beyond traditional disaster management approaches. Unlike standalone prediction systems, this platform combines risk estimation, real-time data analysis, situational awareness, and intelligent response generation to support both authorities and the general public.

The system contributes toward the development of scalable and accessible disaster management solutions by enabling multi-modal interaction, real-time guidance, and data-driven decision-making. It enhances the ability to predict potential risks, analyze on-ground situations, and generate effective response strategies during emergencies.

Overall, the proposed system represents a step toward building intelligent, proactive, and integrated disaster management frameworks that can minimize losses and improve response efficiency in real-world scenarios.

II. LITERATURE REVIEW

Recent advancements in disaster prediction and management have been significantly influenced by developments in Machine Learning, Artificial Intelligence, and data-driven decision systems. This section reviews key contributions related to disaster prediction models, real-time data integration, computer vision-based analysis, and intelligent response systems.

A. Early Disaster Prediction Approaches

Early disaster prediction systems primarily relied on statistical and rule-based methods. Researchers used historical data and predefined thresholds to estimate the likelihood of disasters such as floods and earthquakes. For instance, hydrological models were widely used for flood prediction by analyzing rainfall patterns, river discharge, and water levels.

While these approaches provided foundational insights, they were limited in handling complex and non-linear relationships present in environmental data. Additionally, such systems often lacked adaptability and were unable to incorporate dynamic real-time information, reducing their effectiveness in rapidly changing disaster scenarios.

B. Machine Learning-Based Disaster Prediction

The introduction of Machine Learning techniques significantly improved disaster prediction capabilities. Breiman (2001) proposed Random Forest, an ensemble learning method that enhances prediction accuracy by combining multiple decision trees. Similarly, gradient boosting methods such as XGBoost (Chen and Guestrin, 2016) and LightGBM (Ke et al., 2017) have been widely used for predictive modeling due to their efficiency and high performance.

These models have been applied in flood prediction, earthquake risk analysis, and cyclone forecasting by learning patterns from historical and environmental datasets. Ensemble techniques have shown improved robustness compared to individual models. However, most ML-based approaches rely heavily on static datasets and often fail to incorporate real-time contextual data, limiting their responsiveness in dynamic disaster environments.

C. Real-Time Data Integration and Intelligent Systems

Recent research has focused on integrating real-time data sources such as weather reports, satellite imagery, and news feeds to improve prediction accuracy. Data-driven platforms and web-based APIs enable systems to gather up-to-date information for better situational awareness.

Despite these advancements, many existing systems still lack seamless integration between prediction models and intelligent decision-support mechanisms. The absence of automated interpretation and response generation limits the usability of such systems for non-expert users.

D. Computer Vision for Disaster Analysis

Computer Vision has emerged as a powerful tool for analyzing disaster scenarios. Object detection models such as YOLO (You Only Look Once), introduced by Redmon et al. (2016), enable real-time detection of objects in images with high accuracy and speed. These models have been applied in disaster management to identify affected individuals, damaged infrastructure, and hazardous conditions from visual data.

Although computer vision techniques provide valuable situational insights, their integration into end-to-end disaster management systems remains limited. Most existing works focus on detection tasks without connecting them to decision-making or response planning processes.

E. Large Language Models and Intelligent Response Systems

The emergence of Large Language Models (LLMs) has enabled significant improvements in natural language understanding and generation. Models such as transformer-based architectures have demonstrated strong capabilities in generating human-like responses, summarizing information, and providing contextual insights.

In disaster management, LLMs can be utilized to interpret prediction results, generate safety recommendations, and support conversational interfaces. However, their integration with predictive models and real-time data systems is still an evolving area, with limited implementations in comprehensive disaster management platforms.

F. Limitations of Existing Systems

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Despite substantial progress, existing disaster management systems face several challenges. Many solutions operate in isolation, focusing either on prediction, monitoring, or analysis without providing an integrated framework. The lack of multi-modal capabilities, real-time adaptability, and intelligent response generation reduces their effectiveness in real-world applications. Additionally, limited accessibility features and absence of user-friendly interfaces further restrict their adoption.

III. RESEARCH METHODOLOGY

The development of the **AI-Driven Disaster Prediction and Intelligent Response System** follows a structured methodology that includes requirement analysis, system design, implementation, and evaluation. The primary objective is to build a comprehensive system capable of predicting disaster risks, analyzing real-time data, and providing intelligent response recommendations using Artificial Intelligence techniques.

A. Requirement Analysis

The system is designed to support disaster prediction and emergency response for both the general public and disaster management authorities. Requirements were identified based on existing disaster management challenges and the need for real-time, intelligent decision-support systems.

The main requirements identified were:
• Accurate disaster risk prediction based on location and time inputs
• Integration of real-time external data for improved situational awareness
• Image-based analysis for rescue and hazard detection
• Real-time interaction through a chatbot interface

B. Modular's Design

The system is divided into multiple interconnected modules to ensure efficient processing and functionality:

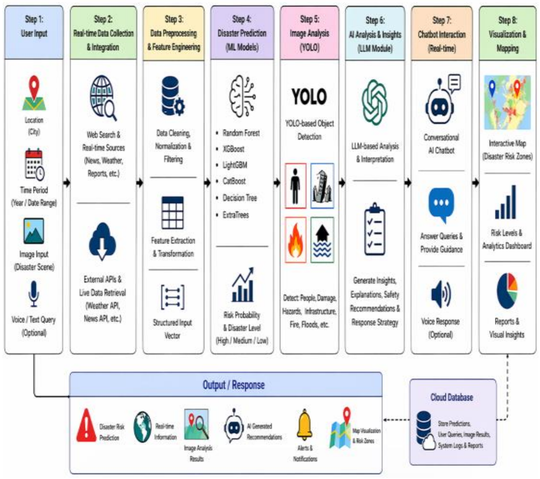
1. **User Interface Module:** A web-based interface enables users to input location, upload images, or provide voice/text queries and receive predictions, analysis, and recommendations in real time.
2. **Disaster Prediction Module:** This module uses trained machine learning models to predict disaster risks based on spatial and temporal inputs such as city and time period.
3. **Real-Time Data Integration Module:** External data sources are integrated using web search APIs to enhance prediction accuracy and provide up-to-date contextual information.
4. **Computer Vision Module:** A YOLO-based object detection model is used to analyze disaster images and identify affected individuals, damaged infrastructure, and hazardous conditions.
5. **LLM-Based Analysis Module:** A Large Language Model processes prediction outputs and real-time data to generate human-readable explanations, safety recommendations, and response strategies.
6. **Chatbot Module:** A conversational AI system enables users to interact with the platform, ask disaster-related queries, and receive real-time guidance.

C. Tools and Technologies Used

Machine Learning Technologies and Algorithms

• **Random Forest:** Used for robust and accurate disaster prediction through ensemble learning.
• **XGBoost / LightGBM / CatBoost:** Gradient boosting algorithms used to improve prediction performance and handle complex data patterns.
• **Decision Tree & ExtraTrees:** Used for fast and interpretable prediction models.
• **YOLO (You Only Look Once):** Used for real-time object detection in disaster images to identify people, damage, and hazards.
• **Large Language Models (LLMs):** Used for interpreting predictions, generating explanations, and providing intelligent recommendations.

D. System Architecture



*T*he proposed **AI-Driven Disaster Prediction and Intelligent Response System** operates through a multi-stage real-time pipeline for predicting disaster risks and generating intelligent response strategies. Initially, the user provides input in the form of location, time period, image data, or voice/text queries. Simultaneously, the system collects real-time information from external sources such as weather reports, news feeds, and online APIs.

The collected data is then processed through preprocessing techniques including data cleaning, normalization, and transformation into structured feature vectors. These processed inputs are passed to multiple machine learning models, which analyze environmental and historical patterns to estimate disaster risk levels such as Low, Moderate, or High.

In parallel, if image input is provided, a YOLO-based computer vision model processes the image to detect affected individuals, damaged infrastructure, and hazardous conditions. The outputs from both prediction and image analysis modules are then integrated and passed to a Large Language Model, which generates human-readable insights, safety recommendations, and response strategies.

Finally, the system delivers results through a conversational AI chatbot, interactive visualization dashboards, and voice-based responses. All outputs are stored in a cloud-based database for future analysis, monitoring, and system improvement. This pipeline ensures a real-time, scalable, and intelligent disaster management solution.

Step1: User Input: User provides location (city), time period, image (optional), or voice/text query.

Step 2: Real-Time Data Collection: System gathers live data from external sources such as weather reports, news, and APIs.

Step 3: Data Preprocessing: Collected data is cleaned, filtered, and converted into structured feature vectors.

Step 4: Disaster Prediction: Machine learning models analyze the data and predict disaster risk levels (Low / Moderate / High).

Step 5: Image Analysis: YOLO-based model detects people, hazards, and infrastructure damage from input images.

Step 6: Intelligent Analysis: Large Language Model interprets outputs and generates insights, safety recommendations, and response strategies.

Step 7: Response Generation: Conversational AI chatbot provides real-time answers and guidance to users.

Step 8: Visualization and Storage: Results are displayed through interactive maps and dashboards, and stored in a cloud database for future reference.

E. Model Training and Validation

The dataset used for training the disaster prediction models consists of historical and environmental data related to floods, earthquakes, and cyclones collected from multiple sources.

Training Process:

• Dataset was preprocessed and divided into training and testing sets.
• Multiple machine learning models were trained using Python-based frameworks.
• Ensemble learning techniques were applied to improve prediction performance.

Evaluation Metrics:

• Accuracy
• Precision
• Recall
• F1-score

Cross-validation techniques were used to ensure model generalization and robustness across different disaster scenarios.

IV. DATASET ANALYSIS

The dataset used in the proposed system consists of historical disaster data, including environmental and geographical parameters such as rainfall, water levels, seismic activity, temperature, and climatic conditions. Additional datasets from sources such as flood records, earthquake databases, and weather reports were used to improve model accuracy and reliability.

A. Pre-processing and Normalization

Before training the machine learning models, several preprocessing steps were applied to ensure data consistency and improve model performance:

• Removal of missing, inconsistent, or duplicate data
• Normalization and scaling of numerical features
• Feature selection based on importance and correlation
• Transformation of raw data into structured input format

To improve robustness, datasets from multiple regions and time periods were incorporated, ensuring better generalization across different disaster scenarios.

B. Model Evaluation

The disaster prediction system was evaluated using standard classification metrics.

Evaluation Metrics:

• Accuracy
• Precision
• Recall
• F1-score

Observations:

• Ensemble models such as Random Forest, XGBoost, and LightGBM demonstrated higher accuracy and stability.
• Environmental features such as rainfall, water level, and climatic conditions played a significant role in prediction performance.
•The system showed consistent performance across different types of disasters and datasets.
•Cross-validation ensured the reliability and generalization capability of the models.

V. EXPERIMENTS AND RESULTS ANALYSIS

This section presents a comprehensive evaluation of the proposed **AI-Driven Disaster Prediction and Intelligent Response System** across multiple components, including disaster prediction accuracy, computer vision performance, and overall system efficiency. The evaluation highlights the system's capability to provide accurate predictions, real-time analysis, and intelligent response generation.

5.1 Experimental Setup

Experiments were conducted using a cloud-based and local development environment, including **Google Colab** and local systems. The machine learning models were trained and evaluated using Python libraries such as Scikit-learn and XGBoost,

while computer vision experiments were performed using the YOLO framework.
The datasets used include:
• Flood prediction dataset (Kaggle)
• NOAA earthquake and weather datasets
• Historical disaster datasets (1990–2023)
The following metrics were used for evaluation:
• Accuracy (%) – Correct predictions of disaster risk
• Precision – Correct positive predictions
• Recall – Ability to detect actual disaster events
• F1-score – Balance between precision and recall

5.2 Comparative Model Performance

The performance of different machine learning models was evaluated to identify the most suitable model for disaster prediction.

Table 1: Performance Comparison of Machine Learning Models

Model	Accuracy (%)	Precision	Recall	F1-Score
Decision Tree	95	0.94	0.95	0.94
Random Forest	98	0.97	0.98	0.97
Extra Trees	100	1.00	1.00	1.00
XGBoost	99	0.98	0.99	0.98
LightGBM	99	0.98	0.99	0.98
CatBoost	98	0.97	0.98	0.97

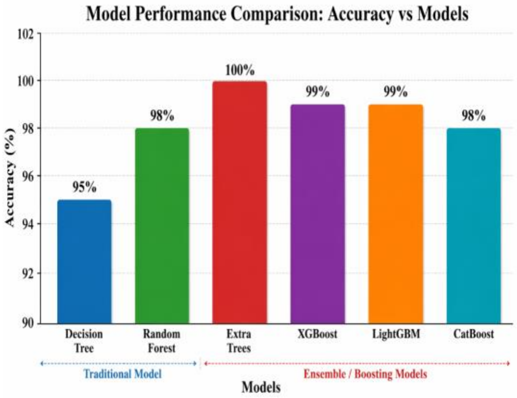
The results show that ensemble models such as Extra Trees and XGBoost achieve the highest accuracy and stability. These models effectively capture complex relationships in environmental data, making them suitable for disaster prediction tasks.

5.3 Visualization of Model Performance

To better understand model performance, graphical analysis was performed.
Suggested Graph:

- X-axis → Models
- Y-axis → Accuracy (%)

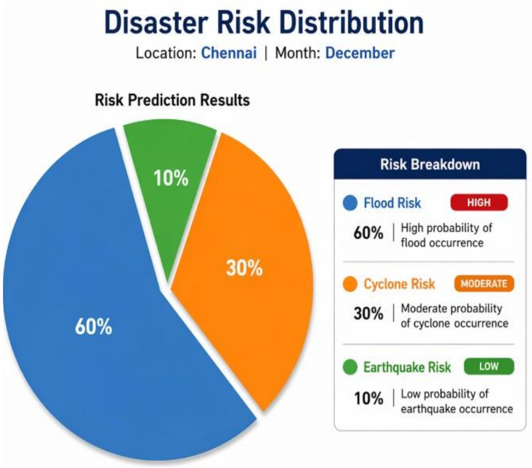
The graph clearly shows that ensemble models outperform traditional models in terms of accuracy and consistency.



5.4 Disaster Prediction Case Study

The system was tested using real-world scenarios to evaluate prediction accuracy.
Example Case:
• Location: Chennai (December)
• Prediction Results:

- Flood Risk: HIGH
- Cyclone Risk: MODERATE
- Earthquake Risk: LOW



This demonstrates the system's ability to provide realistic and meaningful predictions aligned with historical disaster patterns.

5.5 Computer Vision Performance (YOLO Analysis)

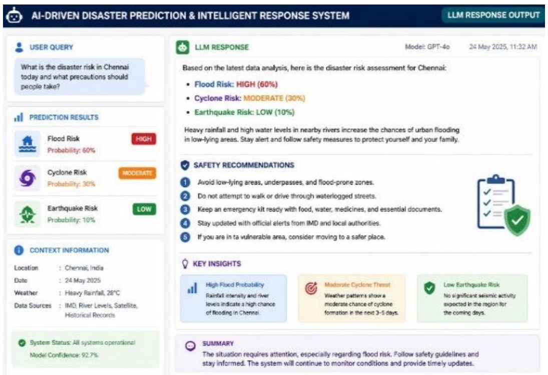
The YOLO-based module was evaluated for its ability to detect objects in disaster scenarios.
Results:
• Accurate detection of people and objects in flood and rescue images
• High confidence scores for detected entities
• Real-time processing capability
Example:
• Chennai flood scenario → 5 people detected → HIGH urgency
• Mumbai flood scenario → 7 people detected → CRITICAL urgency

5.6 System Response and LLM Analysis

The Large Language Model was evaluated for generating meaningful insights and recommendations.

Observations:

- Generated accurate safety instructions
- Provided contextual explanations based on prediction results
- Improved decision-making support for users



5.7 Performance Analysis

The overall system performance was evaluated based on speed, accuracy, and usability.

Module	Response Time (ms)
User Input Processing	120
Data Collection (API)	300
ML Prediction	250
YOLO Detection	400
LLM Response Generation	350
Visualization & Output	150

Observations:

- Fast response time for predictions and chatbot responses
- Efficient processing of real-time data
- Smooth integration of multiple modules

5.8 Key Observations

The experimental results reveal several important insights regarding the performance of the proposed system. Ensemble-based machine learning models demonstrated superior prediction accuracy compared to traditional models, highlighting their effectiveness in capturing complex patterns in disaster-related data.

The integration of real-time external data significantly enhanced contextual awareness, enabling the system to generate more accurate and situation-specific predictions. Furthermore, the YOLO-based computer vision module provided reliable detection of affected individuals and hazardous conditions in disaster scenarios, contributing to improved situational understanding.

In addition, the use of a Large Language Model (LLM) improved the interpretability of prediction results by generating clear explanations and actionable safety recommendations. Overall, the system exhibited strong and consistent performance across multiple disaster scenarios, demonstrating its effectiveness as an intelligent and scalable disaster management solution.

VI. CONCLUSION

A. Key Findings

The proposed **AI-Driven Disaster Prediction and Intelligent Response System** demonstrates the significant potential of Artificial Intelligence in enhancing disaster management, prediction accuracy, and emergency response.

The system successfully integrates:

- Machine learning-based disaster prediction
- Real-time data integration
- Computer vision-based disaster analysis
- Large Language Model-based interpretation
- Conversational AI for user interaction
- Interactive visualization and cloud-based storage

Key achievements include:

- Accurate prediction of disaster risks using ensemble machine learning models
- Real-time analysis of environmental and external data for improved situational awareness
- Effective detection of people, hazards, and infrastructure damage using YOLO-based computer vision
- Intelligent generation of safety recommendations and response strategies using LLMs
- Multi-modal interaction support through text, image, and voice inputs
- Scalable and user-friendly system suitable for both public users and disaster management authorities

Overall, the system demonstrates how integrated AI technologies can transform disaster management from a reactive process into a proactive and intelligent decision-support system.

B. Limitations

Despite promising results, several limitations remain:

1. **Dependence on Internet Connectivity:** The system relies on external APIs and real-time data sources, which may limit functionality in offline or low-connectivity environments.
2. **Limited Real-Time Sensor Integration:** The current system does not incorporate live sensor data such as IoT devices or satellite feeds for real-time monitoring.
3. **Image Quality Sensitivity:** The performance of the computer vision module depends on the quality and clarity of input images.
4. **Model Generalization:** Prediction models are trained on available datasets and may require further tuning for diverse geographical regions.
5. **Limited Large-Scale Deployment:** The system has not yet been tested extensively in real-world disaster management environments.

C. Challenges

During development, several technical and practical challenges were encountered:

• **Data Integration Complexity:** Combining historical datasets with real-time external data required efficient data processing and synchronization.

• **Model Selection and Optimization:** Identifying the most effective machine learning models and tuning them for optimal performance was challenging.

• **Multi-Modal System Integration:** Integrating ML models, computer vision, LLMs, and chatbot systems into a unified pipeline required careful system design.

• **Real-Time Performance:** Ensuring low latency while maintaining prediction accuracy and responsiveness was a key challenge.

• **Interpretability of Results:** Generating meaningful and reliable explanations from model outputs required effective use of LLMs.

D. Future Work

Future research and development will focus on enhancing the system into a fully deployable real-world disaster management platform:

1. **Integration with IoT and Sensor Networks:** Incorporate real-time data from sensors, satellites, and drones for improved prediction accuracy.
2. **Mobile Application Development:** Develop Android and iOS applications for better accessibility and field usage.
3. **Advanced Deep Learning Models:** Explore deep learning and hybrid models for improved prediction performance.
4. **Real-Time Alert System:** Implement automated alert and notification systems for early warning.
5. **Enhanced Computer Vision Capabilities:**Improve detection accuracy for complex disaster scenarios using advanced vision models.
6. **Cloud-Based Scalable Deployment:** evelop a cloud-based platform for large-scale usage and remote accessibility.
7. **Integration with Government Systems:**Collaborate with disaster management authorities for real-world deployment and validation.

E. Conclusion

In conclusion, the proposed **AI-Driven Disaster Prediction and Intelligent Response System** presents a comprehensive and intelligent solution for modern disaster management. By integrating machine learning, computer vision, and large language models into a unified framework, the system enables accurate prediction, real-time analysis, and effective response planning.

The system successfully addresses key challenges in traditional disaster management by providing multi-modal interaction, real-time decision support, and scalable architecture. It demonstrates the potential of AI-driven technologies in reducing disaster impact, improving preparedness, and enhancing emergency response efficiency.

Overall, this research represents a significant step toward building intelligent, proactive, and data-driven disaster management systems capable of supporting both authorities and the general public in critical situations.

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