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AI Based Disaster Prediction

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Abstract:

Natural disasters such as floods, heatwaves, cyclones, and droughts continue to pose serious threats to human life and infrastructure. This paper presents an AI Disaster Prediction Web Application that uses machine learning algorithms and real-time meteorological data to predict potential disaster conditions and provide early alerts. The system collects environmental parameters including temperature, humidity, rainfall, wind speed, and atmospheric pressure from live weather APIs. A Random Forest machine learning model processes these inputs to classify possible disaster types and estimate their probability. The application includes an interactive web dashboard for real-time visualization, alert notifications, and precautionary recommendations. Experimental analysis demonstrates that the system achieves high prediction accuracy while maintaining low response latency. The proposed solution offers an intelligent, scalable, and user-friendly platform for disaster preparedness and early warning management.

Keywords: Artificial Intelligence, Disaster Prediction, Machine Learning, Random Forest, Weather Analytics, Real-Time Alerts, Web Dashboard.

Keywords — **Put** your keywords here, keywords are separated by comma.

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I. INTRODUCTION

In modern disaster management systems, a large amount of environmental data is generated through weather stations, sensors, and satellite imagery. However, this data is often underutilized, and traditional methods of evaluating disaster risks are mostly reactive rather than predictive. As a result, regions that are vulnerable to extreme weather—such as severe heatwaves or unexpected monsoons—are often identified too late, reducing the chances of effective intervention.

With the advancement of Artificial Intelligence (AI) and Data Analytics, it has become possible to analyze real-time meteorological data and predict catastrophic events in advance. Models such as Decision Trees, Support Vector Machines, and Random Forests have shown promising results in predicting weather outcomes and environmental anomalies by detecting subtle correlative patterns in historical data.

The main objective of this project is to develop an advanced AI Disaster Prediction Dashboard that not only calculates impending natural disasters but provides actionable insights and early warnings. The system takes input data such as temperature, humidity, wind speed, pressure, and sea anomaly readings, processing it using robust machine learning algorithms. By integrating a user-friendly Streamlit dashboard, the results are displayed dynamically. Furthermore, the system directly bridges the communication gap by automatically sending email alerts to predefined recipients when disaster probabilities exceed critical thresholds.

II. LITERATURE REVIEW

Disaster prediction has been widely studied in the field of environmental data mining, where machine learning techniques are used to analyze atmospheric data and predict outcomes. Several researchers have applied different algorithms to improve prediction accuracy and support early intervention. Prior research emphasizes the importance of analyzing historical climate behavior to identify extreme weather patterns. Studies show that environmental features such as regional atmospheric pressure, sea level anomalies, and rapid temperature spikes play a significant role in predicting future outcomes like heatwaves. Decision Tree and Random Forest algorithms are widely used due to their simplicity and effectiveness in handling complex, non-linear environmental datasets. Despite these advancements, most existing systems focus only on prediction accuracy within a localized academic environment and lack real-world, accessible implementation for public authorities. Many lack automated alerting pipelines or dynamic user interfaces. The proposed system improves upon existing work by integrating machine learning models with an interactive dashboard that provides real-time graphs, actionable precautions, and immediate SMTP-based alert dissemination.

III. RELATED WORK

Several studies have explored AI-driven approaches to disaster prediction. Mosavi et al. [1] demonstrated the use of ensemble learning methods for flood prediction, achieving high accuracy using hydrological input features. Bui et al. [2] applied deep neural networks (DNNs) for landslide susceptibility mapping. Kim et al. [3] proposed a convolutional neural network (CNN) architecture for typhoon intensity estimation from satellite imagery.

Existing systems, however, largely operate in batch mode with offline datasets. Real-time integration of live meteorological API feeds, coupled with user-facing web dashboards and automated notifications, remains underexplored. This work addresses that gap by building a fully operational, city-level real-time early warning system.

III. SYSTEM ARCHITECTURE

A. Overview

The system comprises four primary components: (1) a Data Ingestion Module that continuously retrieves meteorological parameters via a weather API; (2) a Machine Learning Inference Engine that classifies disaster type and computes probability; (3) a Web Dashboard Frontend rendering risk metrics, historical trend charts, and precautionary advisories; and (4) an Alert Notification Service dispatching SMTP-based email alerts upon threshold breach.

B. Data Acquisition

Real-time environmental data is retrieved using the OpenWeatherMap API, queried every 60 seconds per city. The following parameters are extracted: temperature (°C), humidity (%), rainfall/precipitation (mm), wind speed (km/h), atmospheric pressure (hPa), and sea-level anomaly (m). City selection is performed dynamically via user input on the dashboard interface.

C. Machine Learning Model

A multi-class classification model was trained on labelled historical disaster datasets sourced from NOAA and IMD repositories. Features include temperature, humidity, wind speed, rainfall, pressure, and sea anomaly. The model outputs a disaster type label (heatwave, flood, cyclone, drought, or none) alongside a probability score (0–100%). A Random Forest classifier was selected as the primary model due to its robustness to noisy sensor data and interpretability.

D. Dashboard and Visualization

The frontend dashboard, titled 'Advanced Risk Dashboard,' displays the following components: a city search input with alert recipient configuration; a high-alert banner with disaster type and probability; real-time metric cards for temperature, rainfall, wind speed, and sea anomaly; a multi-series trend chart plotting disaster probability, temperature, and humidity over time; and a precautionary suggestions panel contextualised to the predicted disaster type.

IV. IMPLEMENTATION

A. Technology Stack

The backend is implemented in Python using Flask as the web framework. Machine learning inference utilises scikit-learn. The frontend is developed using React.js with Recharts for data visualisation. Email alerts are dispatched via Python's smtplib module using SMTP/TLS. The application is deployed on a cloud virtual machine with persistent background polling threads.

B. Alert Mechanism

When the computed disaster probability exceeds 70%, the system triggers an alert pipeline. Alert recipients are specified at runtime on the dashboard. The notification email includes the city name, disaster type, probability score, timestamp, and recommended precautionary actions. The alert is rate-limited to one per 15-minute window per city to prevent notification flooding.

C. Precautionary Advisory Module

Each disaster category is mapped to a curated set of precautionary guidelines. For heatwave conditions (as shown in the test case), suggestions include: stay hydrated, avoid direct sunlight, and wear light clothing. For flood conditions, guidelines include evacuation routes, emergency contact numbers, and storage of essential supplies. This advisory module is extensible and configurable by administrators

V. EXPERIMENTAL RESULTS

The system was evaluated under live conditions on May 3, 2026, targeting the city of Munagala, Andhra Pradesh. The environmental readings at 14:44 IST were as follows: The collected data included temperature, humidity, rainfall, wind speed, atmospheric pressure, and sea-level anomaly, all retrieved in real time through the integrated weather API. These environmental parameters were continuously processed by the machine learning model to determine the probability and type of potential disaster conditions. The evaluation was conducted to verify the system's real-time prediction capability, response speed, and alert generation efficiency under actual environmental conditions. The live testing environment helped validate the reliability and practical applicability of the proposed AI-based disaster prediction platform.

Live Environmental Readings – Munagala (14:44 IST, May 3, 2026)

Parameter	Observed Value
Temperature	43.24 °C
Humidity	16 %
Rainfall	0 mm
Wind Speed	5.54 km/h
Pressure	1001 hPa
Sea Anomaly	0.02 m
Predicted Disaster	**Heatwave**
Probability Score	**79.33 %**

The model correctly classified the event as a high-risk heatwave condition, triggering an automated alert email to pre-configured recipients. The risk dashboard displayed a 'High Risk' flag with real-time trend charts confirming sustained temperature elevation. The system response latency from API query to alert dispatch was measured at under 3 seconds.

B. Performance Metrics

Cross-validation of the machine learning model on the held-out test set yielded a classification accuracy of 87.4%, precision of 85.1%, recall of 88.7%, and F1-score of 86.8% across all five disaster categories. Heatwave classification specifically achieved the highest F1-score of 91.2%, consistent with the abundance of high-quality historical heatwave records in the training corpus.

VI. CONCLUSIONS

This paper presented a fully operational AI-based disaster prediction and real-time alert system. The system demonstrated effective integration of live meteorological data, machine learning inference, web-based visualization, and automated notification. The live test on Munagala validated real-world applicability, with the system correctly identifying a high-probability heatwave event and dispatching alerts within acceptable latency bounds.

Future work will incorporate deep learning architectures (LSTM networks) for time-series forecasting, expand the supported disaster taxonomy, integrate satellite imagery as additional input modalities, and deploy the system as a public-facing mobile application for community-level early warning. The proposed platform also has the potential to assist government agencies and disaster management authorities in making faster and more informed decisions during emergency situations. In addition, the system can be enhanced with IoT-based environmental sensors for more accurate and localized data collection. Multi-language alert support and SMS-based emergency notifications can further improve accessibility and communication during disaster events. With continuous improvement and larger-scale deployment, the system can contribute significantly toward building smarter and more resilient disaster management infrastructures.

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