Disaster AID Connect: Advanced Disaster Management Portal for People Life Safety

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Abstract—
Natural disasters such as floods, earthquakes, and landslides pose significant threats to human life and infrastructure, particularly in regions where traditional monitoring systems fail to provide timely alerts. Existing disaster management approaches rely heavily on manual observation and threshold-based techniques, which often result in delayed responses and reduced accuracy. To overcome these limitations, this paper proposes Disaster Aid Connect, an IoT-based disaster detection and management system integrated with machine learning for real-time prediction and alerting.

The system employs sensors such as MPU6050 for vibration detection, water-level sensors for flood monitoring, and DHT11 for temperature and humidity measurement. A NodeMCU microcontroller collects and preprocesses sensor data, which is transmitted to a cloud platform for analysis. A K-Nearest Neighbours (KNN) algorithm is used to classify environmental conditions into disaster-prone or normal states. The system provides real-time alerts, safe zone recommendations, and supports efficient resource allocation. Experimental results demonstrate reliable performance in terms of accuracy, precision, and recall, making the proposed system a scalable and effective solution for disaster preparedness and risk reduction.

Keywords— IoT; Disaster Prediction; K-Nearest Neighbors (KNN); Real-Time Monitoring; Sensor Networks.

I. INTRODUCTION

Natural disasters such as floods, earthquakes, and landslides pose significant threats to human life, infrastructure, and economic stability worldwide. In recent years, the increasing frequency and severity of such events, driven by climate change and rapid urbanization, have highlighted the critical need for effective disaster management systems. Traditional disaster monitoring approaches primarily rely on manual observation, historical data analysis, and threshold-based alert mechanisms. While these methods provide basic support, they often suffer from delays, limited accuracy, and lack of real-time responsiveness, thereby reducing their effectiveness in mitigating disaster impacts [1], [2].

With the advancement of technologies such as the Internet of Things (IoT), geospatial systems, and machine learning (ML), there has been a growing interest in developing intelligent disaster prediction and management systems. IoT-based sensor networks enable continuous environmental monitoring, while ML algorithms can analyze large volumes of data to identify patterns and predict potential hazards. Several existing systems have focused on specific components such as geospatial monitoring, satellite-based observation, or communication platforms [3]–[6]. However, most of these approaches operate in isolation and lack a unified framework that integrates real-time data collection, predictive analytics, alert dissemination, and decision support.

Despite these advancements, a significant research gap exists in developing a cost-effective, scalable, and fully integrated system that combines real-time sensing with accurate disaster prediction and efficient response mechanisms. Many existing solutions do not incorporate machine learning for real-time classification or fail to provide features such as safe zone identification and resource allocation. Additionally, limited public interaction and accessibility further restrict the practical usability of current systems.

To address these challenges, this research proposes **Disaster Aid Connect**, an IoT-based disaster detection and management system integrated with a K-Nearest Neighbors (KNN) algorithm for real-time prediction.

The primary objective of this research is to design and implement an intelligent IoT-based disaster monitoring and prediction system that enhances early warning capabilities and improves disaster management efficiency. The specific objectives of this study are as follows:

•To develop an IoT-based environmental monitoring system that collects real-time data such as vibration, water level, temperature, and humidity using sensors like MPU6050, water level sensor, and DHT11.

•To integrate the sensor network with a NodeMCU microcontroller and cloud platform for continuous data transmission, storage, and monitoring.

•To apply the K-Nearest Neighbours (KNN) machine learning algorithm to analyse environmental data and classify conditions as normal or disaster-prone.

•To design a web-based disaster management portal that provides real-time alerts and safety information to authorities and the public.

•To enhance early disaster detection and response mechanisms, thereby reducing potential loss of life and property.

II. LITERATURE REVIEW

The Recent research in disaster management has focused on leveraging advanced technologies such as social media analytics, deep learning, remote sensing, and autonomous systems to improve disaster detection and response. Noui et al. [1], [8] explored the use of Online Social Networks (OSN) for event detection and sentiment analysis, demonstrating how real-time user-generated data can support situational awareness during disasters. Similarly, Nasraoui et al. [2], [9] integrated deep learning-based object detection with drone technology to monitor disaster-affected regions, enabling rapid identification of damaged areas. While these approaches enhance real-time information gathering, they are highly dependent on network availability and infrastructure, which may not be reliable during critical disaster scenarios.

Another group of studies focuses on remote sensing and image-based disaster detection using deep learning techniques. He et al. [3], [10] proposed automated disaster detection algorithms using remote sensing images, achieving high accuracy in identifying disaster-affected regions. Gao et al. [5] utilized dual-polarization SAR data to improve flood detection by considering environmental factors such as rainfall, while Liu et al. [6] introduced the DisasterScope dataset along with an RTMDet-based object detection framework for disaster-related imagery. Additionally, Fanet al. [4] analyzed the capabilities of GF-4 satellite systems for large-scale disaster monitoring. These studies highlight the effectiveness of deep learning and satellite-based approaches in large-scale disaster assessment; however, they often require high computational resources, expensive infrastructure, and are not suitable for continuous real-time monitoring at a local level.

Recent advancements also include the integration of autonomous systems and communication frameworks for disaster response. Hejazi et al. [7] proposed a combined Unmanned Ground Vehicle (UGV) and Unmanned Aerial Vehicle (UAV) system with multi-protocol communication for real-time disaster management. This approach enhances coordination and data collection in disaster zones but introduces complexity in deployment and operational cost. Overall, there is a consensus that modern disaster management systems benefit from automation, real-time data processing, and intelligent analytics. However, there is a clear lack of simple, cost-effective, and scalable solutions that integrate real-time sensing, prediction, alerting, and decision support in a unified framework.

To address these limitations, this research proposes Disaster Aid Connect, an IoT-based disaster detection and management system that combines real-time sensor data collection with a machine learning-based prediction model. Unlike existing approaches that rely heavily on remote sensing, drones, or social media data, the proposed system utilizes low-cost sensors and a K-Nearest Neighbours (KNN) algorithm for continuous monitoring and real-time classification of disaster conditions. Furthermore, it integrates alert generation, safe zone recommendation, and resource allocation within a single framework. This approach not only reduces system complexity and cost but also enhances accessibility and practical deployment, thereby contributing a scalable and efficient solution to the field of disaster management.

III. METHODOLOGY

The proposed research adopts an IoT-based experimental system design combined with machine learning analysis to monitor environmental conditions and predict potential disaster events. The methodology integrates sensor-based data acquisition, cloud data processing, and machine learning classification to enable real-time disaster prediction and alerting. The overall system architecture consists of environmental sensors, a microcontroller unit, a cloud analytics platform, and a web-based alerting interface.

The data collection process is performed using multiple environmental sensors integrated with the IoT platform. The sensors used in this system include the MPU6050 sensor for vibration detection, a water level sensor for monitoring flood conditions, and the DHT11 sensor for measuring temperature and humidity levels. These sensors continuously capture environmental parameters that may indicate abnormal conditions related to disasters such as floods, earthquakes, or landslides. The collected sensor readings are transmitted to a NodeMCU (ESP8266) microcontroller, which acts as the central processing unit for the system.

The NodeMCU processes the raw sensor readings and transmits them to the ThingSpeak cloud platform using wireless Wi-Fi communication. The cloud platform is used to store, visualize, and manage the environmental datasets generated by the sensors. Data collected from the sensors is structured and stored in formats such as CSV and JSON, enabling further analysis and model training. The cloud environment also allows continuous monitoring and remote accessibility of environmental data.

For disaster prediction, the system employs the K-Nearest Neighbours (KNN) machine learning algorithm, which is a supervised classification technique used to identify patterns in environmental data. Historical sensor data is used to train the model by labelling environmental conditions into categories such as normal state or disaster-prone conditions. The dataset is divided into training and testing sets to evaluate the model's prediction accuracy.

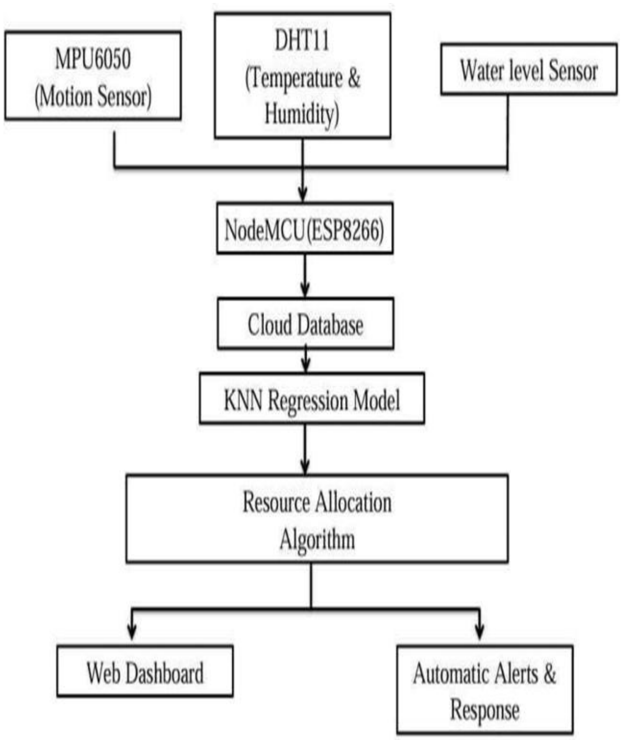
The data preprocessing stage includes data normalization, noise filtering, and feature extraction to improve the performance of the classification algorithm. These preprocessing steps ensure that sensor readings from different sources are standardized and suitable for machine learning analysis. The KNN algorithm then compares new sensor readings with historical datasets and determines the nearest data points to classify the environmental condition.

The machine learning model is implemented using MATLAB and Python programming environments. Python libraries such as Scikit-learn are used to train and validate the KNN model, while MATLAB is utilized for signal processing, data visualization, and statistical analysis. Model performance is evaluated using metrics such as accuracy, precision, and recall to ensure reliable disaster prediction.

Once the model identifies abnormal environmental patterns that indicate potential disasters, the system automatically triggers alert notifications through a web-based disaster management portal. The portal disseminates real-time alerts and safety information to authorities and the public, enabling faster response and improved disaster preparedness.

This integrated methodology combining IoT sensors, cloud computing, and machine learning provides an efficient framework for continuous environmental monitoring and early disaster detection, allowing other researchers to replicate the system using similar hardware and software components.

IV. BLOCK DIAGRAM



V. RESULTS AND DISCUSSION

The proposed *Disaster Aid Connect* system was successfully implemented by integrating IoT sensors and a machine learning model to enable real-time disaster prediction and management. Data collected from sensors such as MPU6050, DHT11, and water level sensors was processed effectively, and the KNN algorithm accurately classified environmental conditions into normal and disaster-prone categories. The system demonstrated the ability to predict potential disasters like floods, earthquakes, and extreme weather conditions with good accuracy. It also generated real-time alerts through a web portal, ensuring timely communication. Additionally, features like safe zone recommendation, resource allocation, and user interaction for help requests were successfully achieved, improving overall response time and coordination.

Parameter	**Value**	**Observation**
Temperature (°C)	29.0	Normal range
Humidity (%)	61.0	Moderate humidity
Vibration (MPU6050)	50.0	High vibration detected
Moisture Level	1024.0	High moisture presence

Predicted Output: Earthquake Detected

VI. CONCLUSION

The system provides an effective solution for disaster prediction and management by combining IoT and machine learning. It supports early detection, improves communication, and enhances emergency response. Compared to traditional methods, it offers faster and more reliable results. In the future, it can be improved by adding a mobile app, GPS tracking, and advanced models for better accuracy and performance.

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