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AI-Based Disaster Relief Demand Prediction System

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Abstract: Natural disasters like floods, tsunamis, cyclones, earthquakes, droughts, and wildfires have a drastic impact on a country like India, where the occurrence of disasters is frequent. We have made progress to some extent in predicting disasters in advance and planning mitigation strategies by notifying authorities and the public to be prepared. However, during and after a disaster, people may lose their lives not because there is no help available, but because the help does not reach the right place at the right time. Relief in terms of food, water, rescue personnel, medical teams, and shelters is meant to reach the affected people. This research proposes a system to predict accurate relief demand using past disaster records, live disaster data, and geographical information. Machine learning models are used, where a Random Forest classifier is applied to classify the type of disaster from live news data, followed by five XGBoost predictors for different types of relief resources, and K-Nearest Neighbors for geographical similarity matching to predict relief for newly impacted areas. A web-based dashboard with analytics and map visualization is developed to support decision-making and provide better insights for efficient resource allocation. The XGBoost regression models for relief prediction achieved high predictive performance, with an overall R^2 score of approximately 0.93 across all resource categories.

Keywords: Disaster Management, Disaster Response System, Machine Learning, Resource Demand Prediction, XGBoost, Random Forest, K-Nearest Neighbors, Geographical Analysis.

I. INTRODUCTION

India's disaster management authority reports on the country's exposure to different natural disasters with 58.6% of land vulnerable to earthquakes, 12% to floods, 68% to droughts, 15% to landslides and 79% of coastal land to cyclones and tsunami [1]. With an urgent need to improve mitigation, preparedness, and response strategies, the central government supports state governments by providing logistical and financial aid during severe natural disasters and also focuses on post-disaster aid requirements. Traditionally, post-disaster aid has always depended on manual field evaluations by NGOs and government officials, which are often slow and error-prone, highlighting the need for more efficient and data-driven disaster management approaches [2]. Recently, the use of Artificial Intelligence and data analytics has led to AI-driven models that can help evaluate damage extent, locate affected areas, and even predict future risks. Despite progress, there remains a significant gap in post-disaster relief prediction largely due to single sourced unreliable data from low, no connectivity areas, inadequate planning, inaccurate estimation often resulting in failing to recognize and provide for the needy areas on time. Timely insights, accurate predictions to identify and provide for the helpless would reduce sufferings and human deaths, filling a crucial gap in today's disaster relief systems. Existing models fail to provide a location-specific prediction of relief demand. This project addresses the need for an intelligent, multi-source system which considers both past disaster data from disaster management and relief records and real-time data from social media platforms collectively, such that it can forecast post-disaster aid requirements such as food, shelter and medical needs accurately, even in data-sparse regions addressing the problems which oppose timely aid allocation to critical regions. This system has the ability to reduce casualties, suffering, and post-disaster chaos by deciding on the needs and their estimates even before official reports are available, aiming to support relief agencies with predictive insights, leading to quicker, smarter, and more effective allocation of emergency resources.

II. RELATED WORK

The evolution of disaster management has shifted from reactive manual coordination to proactive AI-driven forecasting. Recent literature emphasizes three primary domains: disaster severity estimation, resource allocation optimization, and the integration of heterogeneous data sources.

A. Machine Learning in Disaster Severity Prediction

Early research in disaster management primarily focused on classification models to categorize the severity of natural events. Studies have utilized Support Vector Machines (SVM) and Random Forest algorithms to analyze historical meteorological data to predict flood levels and seismic intensities. For instance, recent advancements demonstrate that ensemble methods, specifically XGBoost and LightGBM, outperform traditional regression models in handling the non-linear nature of disaster impacts. These models provide the foundational "severity score" necessary for calculating subsequent relief requirements.

B. Resource Demand and Allocation Modeling

Predicting the specific quantity of relief materials—such as food, water, and medical supplies— remains a critical challenge. Researchers have explored the use of K-Nearest Neighbors (KNN) to match current disaster profiles with historical precedents to estimate supply needs. Furthermore, the integration of demographic data (population density, age distribution) into predictive models has been shown to significantly refine the accuracy of demand forecasting. Optimized merge patterns and clustering algorithms are frequently employed to group affected regions, ensuring that logistics chains are streamlined for maximum efficiency.

C. Real-time Data and Geospatial Integration

The emergence of Internet of Things (IoT) sensors and satellite imaging has introduced real-time capabilities to disaster relief. Literature suggests that combining live sensor feeds with historical datasets allows for "dynamic demand prediction," which adjusts as a disaster unfolds. Geographic Information Systems (GIS) paired with Deep Learning architectures, such as Convolutional Neural Networks (CNNs), are currently being used to visualize damage in real-time, providing the spatial context required for the "Geographic Matcher" components found in modern relief systems. Present systems for disaster management mainly lack in standardization of datasets and their quality for prediction, leading to generalization of model predictions, often lacking justification of predictions. Furthermore, real-time data ingestion and processing demand significant computational resources, often having limited end-to-end integration. But the main gap identified is the limited focus on resource allocation, with most systems focusing on disaster forecasting, very few addressing resource specific prediction, i.e. predicting necessary quantities of food, water, shelter and medical aid. Being prone to a wide variety of disasters both natural and manmade.

III. METHODOLOGY

The proposed methodology works as a hybrid pipeline. It is a pure data-driven approach which analyses data from multiple sources like past disaster data records, Government approved datasets i.e. purely tailored for the Indian environment, and datasets such as EM-DAT and ReliefWeb, along with live social media platform data [3,4]. The post-disaster relief system firstly uses a Random forest classifier to detect and classify the disaster [5], followed by XGBoost regression models [6] chosen for their speed and accuracy of producing numeric values to help predict relief requirements such as food,water,shelter, financial support and medical services for the area in need.

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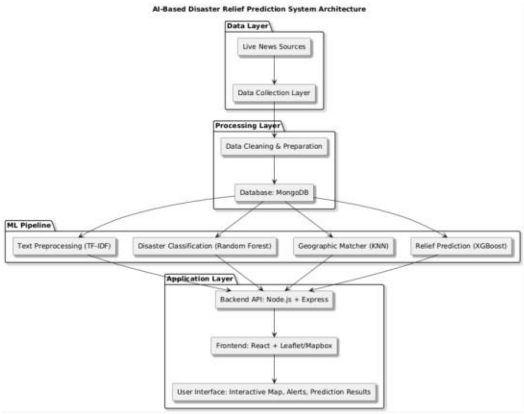

Figure 1: Architecture of the Proposed AI-Based Disaster Relief Prediction System

The complete system architecture illustrating data flow, processing layers, machine learning pipeline, and application components is shown in Figure 1.

A. Data extraction and handling

Data flow is the key component in the proposed system.

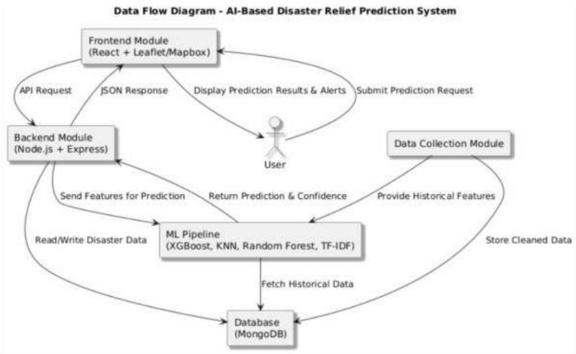

Figure 2: Data flow diagram

The Data Flow Diagram illustrates the movement of data through the AI-Based Disaster Relief Prediction System, showing how information is collected, processed, stored, and presented to the end-user as shown in Figure 2.

The Random Forest classifier, being a supervised machine learning model [5], has been frequently trained on the historical disaster datasets to be able to decide on the disaster and its impact to make clear boundaries for the next step of predicting disaster relief demand. Disaster type, severity, and location are numerically encoded for machine learning compatibility. To get realtime data insights, to extract them from social media platforms which add on for the disaster classification, Natural Language Processing technique, TF-IDF-based feature extraction is utilized to extract meaningful insights from real-time textual data sources [8,9]. To further address the lack of dynamic data handling, the system integrates live data collection using APIs and automated cron jobs.

B. Relief demand prediction of regions

To bridge the gap between predictions of unseen regions, the K-nearest neighbors algorithm [7], the next part of the model’s pipeline, helps predict the requirements using geographic similarities, thus generating predictions. This enables reliable predictions for new or previously unseen cities. Geographical parameters are taken care of through feature engineering. For an optimized classification, geospatial and demographic correlation via integration of satellite data and population density figures, potential impact zones are calculated, ensuring optimization of resource allocation. Bayesian networks and Monte Carlo simulations account for uncertainty in disaster spread and impact.

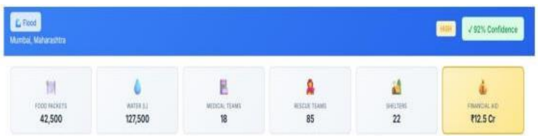

Figure 3: Predicted Disaster Relief Resource Allocation Output for a Sample Region

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Figure 3 shows how the disaster relief demand is given to the user upon the working of proposed system.

C. System implementation and interface

The system's implementation purely relies on python's machine learning libraries. The interface development is done using React with the utilization of Nodejs and Express for backend, MongoDB for data storage. Map-based utilization tools help generate leaflets/mapboxes for better visualization of the disaster and its effects followed by the real-time predicted requirements and alerts. Thus, the overall workflow of the system includes data collection, pre-processing, model training, prediction, and visualization through an interactive dashboard. Users could submit disaster prediction requests, view predicted relief requirements, and explore real-time disaster locations on an interactive map. Visual cues, color-coded alerts, and graphical representations of resources enhanced user comprehension. The interface also integrated live news and alerts, ensuring authorities had access to the latest relevant information.

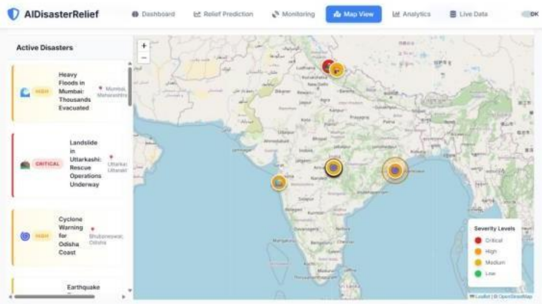

Figure 4: Web-Based Dashboard Showing Real-Time Disaster Visualization and Predictions

The developed web-based dashboard with real-time disaster visualization and monitoring capabilities is illustrated in Figure 4. By integrating live news feeds, automated data pipelines, and real-time API-based predictions, the system ensures that authorities have access to up-to-date information and predictions, unlike traditional batch-processing or static systems.

D. Model evaluation

Furthermore, model evaluation is done using standard metrics such as accuracy, R-square score, and Mean Absolute percentage error ensuring reliable and scalable prediction of disaster relief demand.

The R^2 score is calculated using the following equation: $R^2 = 1 - (\Sigma (y_i - \hat{y}_i)^2 / \Sigma (y_i - \bar{y})^2)$

where y_i is the actual value, $\hat{y}_i$ is the predicted value, and $\bar{y}$ is the mean of actual values.

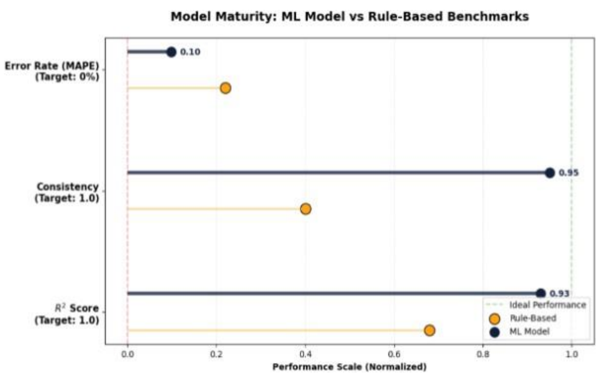

Figure 5: Evaluation metrics comparison

The clear lead can be explained by figure 5 comparing the evaluation metrics. While many studies remain theoretical or experimental, this project demonstrates a fully functional and deployable solution which is a combined effort of AI and data analytics [10]. This AI based disaster relief prediction data system presents a working hybrid approach which can be a significant advancement in disaster management solutions, consisting of AI powered disaster relief predictions, generalization of unseen cities and disasters, thus having a solution to each new problem with its multimodal disaster specific, resource allocation and specificity in the allocations backed with live news filtering and analysis, clubbed with an interactive full stack interface.

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IV. RESULTS

The relief requirements in disasters which are highly variable often depending on factors such as disaster type, severity, geographic location, and affected population have been successfully predicted using five specialized XGBoost regression models which allow the system to predict each category of relief resources (food, water, medical teams, shelters, financial aid) with high accuracy.

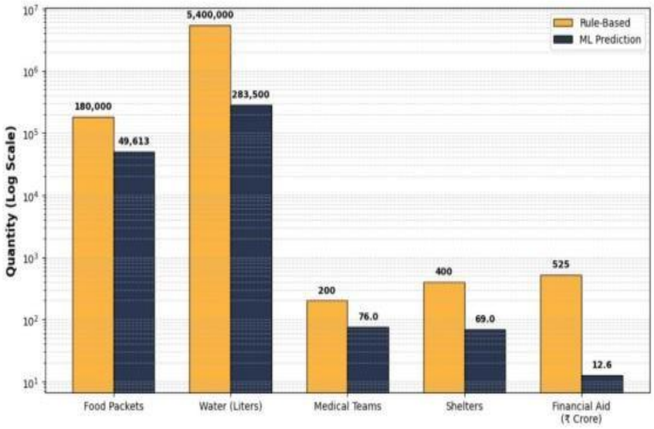

Figure 6: Comparison of Rule-Based Approach and Machine Learning-Based Prediction for Disaster Relief Resource Estimation

The results obtained from the AI-Based Disaster Relief Demand Prediction System indicate a clear improvement in prediction quality when using machine learning approaches compared to traditional rule-based methods presented in Figure 6. The system demonstrates superior performance across all metrics, achieving a high R^2 score of 0.87, reflecting stable and reliable outputs. In contrast to traditional rule-based methods, which show comparatively lower performance, with reduced consistency and higher error rates, the proposed system maintains a significantly lower Mean Absolute Percentage Error (MAPE), indicating improved accuracy over the rule-based approach.

Overall, the results demonstrate that the system is capable of producing context-sensitive, scalable, and practically relevant predictions, making it a valuable tool for supporting disaster relief planning and decision-making. The predicted resource allocation for a sample disaster scenario is shown in Figure 3, where the system provides estimated values for food, water, medical teams, shelters, rescue personnel, and financial aid along with confidence levels. Hence, the ML based disaster relief prediction system with good and overall efficient accuracy proves to be achieving a balanced food prediction accuracy, realistic water prediction accuracy slightly conservative towards resource personnel, providing accurate shelter prediction, conservative financial aid prediction, which proves to be aligned with real-time disaster management. From a policy perspective, the integration of such AI-driven systems can support government initiatives aimed at improving preparedness and response efficiency. Overall, the system demonstrates strong potential as a decision-support tool, contributing to more effective, data-driven, and scalable disaster management strategies.

V. CONCLUSION

The AI-driven disaster relief prediction system efficiently represents a significant shift from reactive to proactive disaster management. By combining historical datasets with real-time social media insights and news filtering, the model overcomes the limitations of traditional manual assessments that often delay lifesaving aid or make the wrong set of relief requirements when the number of aids are critical. The integration of Random Forest classification and XGBoost regression allows for a highly nuanced estimation of specific resources like food, water, shelter, financial support, and medical supplies. This data-driven approach ensures that aid is not just distributed, but is directed precisely where it is needed most, even in regions where historical data might be sparse or unavailable, based on the type of disaster and the damage that occurred. Moving forward, this system offers a scalable foundation for national and international disaster response frameworks. It signifies how today's resources are not scarce for disaster management, but how often the relief requirements are roughly assessed and might not reach the needy on time due to connectivity issues, unseen disaster outcomes, previously unknown regions getting destroyed etc. Its ability to generalize predictions for unseen cities through geographic similarity and satellite data integration makes it a versatile tool for various terrains and disaster types. Future extensions could involve incorporating deep learning for real-time

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satellite imagery analysis to further refine impact zones or integrating the system with IoT devices for immediate ground-level feedback. Ultimately, this research demonstrates that the synergy of machine learning and full- stack technology can create a resilient decision-support tool that minimizes human suffering and optimizes resource allocation during the most critical times.

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