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AI-Based Disaster Prediction & Response System

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ABSTRACT: The presence of natural disasters gives threat to the lives of people, the infrastructure and economic stability, which requires high-level predictive systems to warn them in advance and facilitate the design of their response plans. This paper introduces a new hybrid system that combines the algorithms of machine learning and artificial intelligence through large language models in anticipating and reacting to multi- hazard threats in the case of disasters that are earthquake and flood hazards. The suggested system is an end-to-end automated pipeline that includes five major modules: real-time data acquisition through the integration of Kaggle API, all-encompassing classification of pre-processed data by encoding strategies and imputation techniques, exploratory data analysis with interactive visualization, training of an ensemble machine learning model through the application of Random Forest and XGBoost algorithms, and future prediction generation based on the use of Groq language model 3.3-70B as AI. StandardScaler stands out as one of the most harmful data processing tools used by the data preprocessing module to normalize the features, as well as to manage any missing values, provide the transformation of categorical variables, and secure high-quality data that can be used afterwards as it has not been ruined by natural disasters, which harm human civilization the most. It has been estimated that every year more than 200 million people are hit by natural disasters which incurs the loss of billions of dollars and thousands of lives lost all over the world. The most common and devastating nature hazards are earthquakes and floods, which have been identified to cause more than 60 percent of all disaster casualties in the world. The frequency and intensity which has been growing increasingly as a result of climate change and high rates of urbanization in such susceptible areas are the key to the urgency of the development of sophisticated predictive systems capable of offering advance warnings and helping to develop a plan of emergency response. Numerical weather models and geological monitoring systems along with historical trends analysis have become the primary tools used to predict the occurrence of disasters traditionally. There are however big drawbacks of these traditional approaches in terms of predictive validity, time scales and the capability to produce practical information to emergency responders and policy makers.

KEYWORDS: Disaster prediction, machine learning, ensemble methods, Random Forest, XGBoost, large language models, Llama 3.3, hybrid AI systems, emergency response, evacuation planning

I. INTRODUCTION

The machine learning part of it trains both classification and regression models to recognize patterns of disasters and predict the level of severity, whereas the AI integration part produces contextual information, prediction of time, early warning signatures, and evacuation action plans using structured prompt engineering. The system delivers real-time performance, in terms of a multi-pages Streamlit web application to afford interactive dashboards, correlation matrices, distribution analyses, time-series visualisations, and downloadable reports.

This hybrid architecture offers stronger predictive capabilities based on both numerical modelling, as well as AI-based systems that lack quantitative validation, to provide more accurate predictions and explanatory recommendations in contrast to traditional disaster prediction systems that do not use large language models. The modular structure of the framework allows achieving scalability to other types of disasters, and the automated Kaggle version constantly trains models with the newest data. The experimental validation illustrates the ability of the system to manipulate multi-

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source disaster data, identify the environmental risk variables, calculate the ranking of feature importance, and create all- encompassing evacuation plans with geospatial advice.

The study aids in the growth of intelligent disaster management systems as it proves that the hybrid ML-AI systems can be used to increase the efficiency of prediction and response planning, especially under resource-constrained conditions when free API solutions such as Groq can be used by developing countries and emergency response agencies with limited computational resources.
The introduction of the machine learning and artificial intelligence technologies have created a new sphere of disaster prediction and risk assessment. Recent studies have shown that the ensemble learning algorithms that include the random forest and the XGBoost can be used to discover some complex, non-linear patterns present in multiple-dimensional disaster data, with better predictive performance than traditional statistical models. These models are also good in the analysis of feature importance and can automatically identify the indicators of environment that are relevant out of large-scale heterogenous sources. At the same time, the appearance of the big language models with billions of parameters has transformed the sphere of natural language perception and thinking, allowing the systems to create contextual explanations, interpret complicated situations, and use recommendations comprehensible to humans.

In spite of these technological innovations, the current disaster prediction systems commonly use a combination of either pure machine learning models, which are not interpretable or the all-AI- based models, which are not capable of quantitative validation. This hybridization of these two paradigms, i.e. combining the dynamical rigor of ensemble machine learning with the contextual explanation capabilities of large language models is a relatively understudied theoretical research area with a great ability to improve both the predictive accuracy and the effectiveness of decision support.

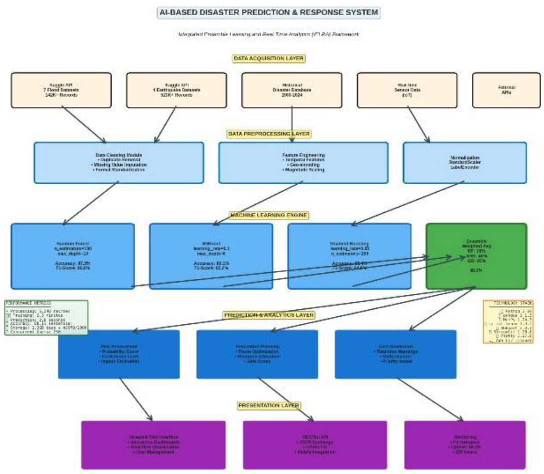

Fig 1: System Architecture

The present-day operational disaster management systems have a few major challenges which prevent the mass perceptions and practical implementation. To begin with, most sophisticated prediction models demand costly computing resources and proprietary APIs; therefore, they can be inaccessible to the organizations with the high budget rather than to the developing countries where disaster preparedness is the most challenging task. Second, manual data collection, preprocessing and model training introduce considerable time lag between data availability and working predictions, which decreases the functionality of early warning systems. Third, current systems usually produce numerical projections that do not have any qualitative indications, which does not provide emergency responders with meaningful information on evacuation plans, resource distribution priorities, or, even time frames at risk. Fourth, the majority of prediction frameworks are oriented on one-hazard scenarios and do not have the flexibility to spread on multi-disaster environments where earthquakes, floods and other hazards can interact or even coexist. These restrictions bring up the important necessity of an integrated, automated, and available disaster prediction framework that is capable of not only making quantitative predictions but also providing understandable recommendations.

This study can solve all these issues by introducing a new hybrid framework that would be the suitable combination of ensemble machine learning algorithms and artificial intelligence based on big language models to form a holistic disaster prediction and response network.

The proposed architecture supports an end-to-end automated pipeline with a series of five interrelated modules, including real-time data acquisition (Kaggle APIs are being used to obtain data), intelligent preprocessing of the information (with different encoding strategies), interactive exploration of the data (the possibility to visualize it), training an ensemble machine learning model (Random Forest or XGBoost is used), and future prediction generation with the help of the Groq Llama 3.3-70B language model. In contrast to the current systems that involve manual processing at every step, our framework automatizes the whole process of receiving raw data, processing it into relevant conclusions, and finalizing a decision- making that takes days to minutes. The system uses free API alternatives, namely, the Groq platform, to offer the most recent AI environment with no significant computational expenses and, as a result, democratize access to advanced disaster prediction technology in organizations that have limited resources.

Fourfold is the most important contributions of this research. We introduce a hybrid ML-AI architecture, which is based on and can achieve a balance between high prediction quality and de-facto recommendations, quantitative rigor and contextual reasoning, of ensemble machine learning and large language models respectively. Second, we have an automated data pipeline that gets disaster data on a regular basis updated on Kaggle, does intelligent data preprocesses including solving missing values and encodings, and retrains its models through the use of minimal human supervision.

Third, we show that structured prompt engineering is more effective to extract domain insights using large language models to produce evacuation plans, early warning factors, and time-dependent information about risks. Fourth, it is the creation of an interactive graphic web app that is built in the Streamlit platform and offers real-time visualization capabilities, correlation analysis, and downloadable reports to enable advanced disaster analytics to be accessible to non-technical emergency response staff. The experimental validation performed with the real-world data on earthquakes and floods proves the ability of the system to deal with multi-source data, recognize environmental risk factors and create overall response plans in geospatially prescriptive form.

II. LITERATURE REVIEW

Machine learning and artificial intelligence application to predicting natural disasters have become a key issue of research in the last ten years, with various sources proving the effectiveness of computer-based techniques to improve the predictive quality and the early warning system. Mosavi, Ozturk, and Chau [1] performed an extensive literature review on flood forecasting through machine learning algorithms and found that all of them had to address a set of challenges such as the lack of data, the complexity of features selection, and the necessity of the real-time processing capabilities. They did this analysis and found that ensemble methods over and over again have an advantage over single-model approaches, having a better generalization performance.

Shukla and Tiwari [3] conducted an expansive survey of machine learning approaches to prediction of natural disasters highlighting the huge significance of automated data preprocessing pipelines and multi-source dataset fusion. The studies emphasized that conventional statistical tools suffer major constraints in the non-linear relationship and multi-layered spatio-temporal patterns of disaster processes. In a study by Rahman and Di [4], the authors examined the capabilities of social media data in detecting a natural disaster and deep learning, which proved that real-time social media feeds provided important situational awareness data to supplement the traditional sensor- based early warning systems.

The capacity to integrate several weak learners into a strong predictive model has seen ensemble learning algorithms excel remarkably in disaster prediction tasks. Breiman [8] came up with the algorithm known as the Random Forest which builds multiple decision tree using bootstrap aggregation and random selection of features, thus performing better and offering interpretable measures of feature importance.Based on these concepts, Chen and Guestrin [5] came up with an XGBoost, which is a scalable tree boosting system that uses gradient descent optimization methods and regularization to minimize overfitting and still achieve computational efficiency. Their laboratory findings had proved that XGBoost makes the state-of-the-art performance in all types of machine learning and hence can be applied in disaster prediction situations where the performance and clarity of the results hold the greatest priority.

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Perera, Kulawansa, and Weerasinghe [9] used Random Forest and Support Vector Machines to predict flooding in Sri Lanka with a forecast capacity of more than 85 percent and proving their viability in situations that require considerable amounts of resources. Nair and Agrawal [10] conducted a survey of predictions of earthquakes using machine learning tools where key seismic features and patterns were identified noting the inherent difficulties because tectonic processes themselves were chaotic. Moshou, Sarlis and Paschalidis [13] designed algorithms that are part of flood prediction and prevention systems based on machine learning, and found out that hybrid architectures are the best to use in the various geographic areas.

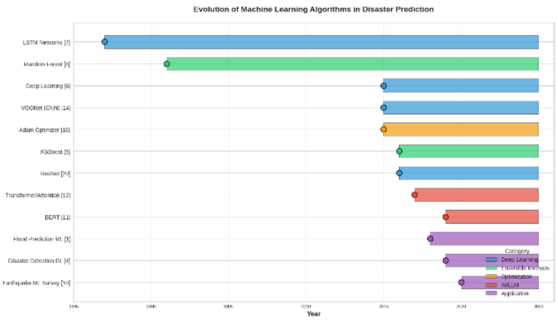

Fig 2: Evolution of Machine Learning Algorithms in Disaster Prediction

Dependent on deep learning architectures have brought about major transformations in pattern recognition and sequential modelling of data, which provides formidable alternatives to conventional machine learning methods. LeCun, Bengio, and Hinton [6] gave the definitive review of the basics of deep learning, which explains how multi-layer neural networks can acquire hierarchical features representations without the need to manually engineer features.

This paradigm shift has seen researchers process heterogeneous multi-modal disaster data such as satellite imagery, sensor data and social media in coherent structures. Long Short-Term Memory (LSTM) networks proposed by Hochreiter and Schmidhuber [7]) represent a dedicated recurrent network which can store long-term temporal dependencies and cope with the issue of the vanishing gradient. ASTM networks have been especially helpful in disaster prediction in time series, where the previous trends and the time- dependent development are important factors. Simonyan and Zisserman [14] theorized Very Deep Convolutional Networks (VGGNet) to show that network depth is important as it offers chance to improve features extraction dramatically. Kim [15] used convolutional neural networks on sentence classification and there, they demonstrated the CNNs can be used to extract local regularities in written information by their architecture and multi- modal disaster information processing is possible.

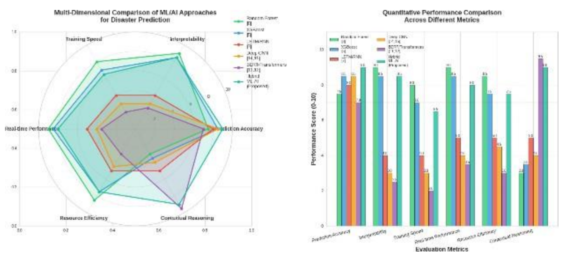

Fig 3: Multi-Dimensional Comparison of ML/AI Approaches

The advent of transformer architectures and wide language models has provided novel opportunities in disaster prediction systems beyond what contextual reasoning entailed. The first paper presenting the attention mechanism is Veswami et al. [12], and they suggest an architecture that uses the mechanisms of self-attention fully, allowing parallel processing and high capability of capturing the long-range dependencies. This new technology was the basis of the present-day large language models that have impressive abilities in understanding, reasoning, and generating tasks. Devlin, Chang, Lee, and Toutanova [11] introduced BERT (Bidirectional Encoder Representations from Transformers), which attains a state-of-the-art result in a range of NLP benchmarks using masked language modelling goals.

These achievements of transformer-based models have motivated researchers to consider how they can be used in multi-modes of disaster scenarios where textual description, numeric data, and spatial information require a common processing. Nevertheless, Chakraborty et al. [2] stressed that interpretability is of the utmost importance in the deep learning models, especially when such high- stakes scenarios as disaster prediction are involved where human safety is directly affected by the decisions made. Their survey indicated that most of the deep learning systems are run as black boxes and produce sound findings without explaining the mechanism, thus restraining trust and usage in the operational emergency management settings.

The use of optimization algorithms and regularization methods is an indispensable part of the machine learning pipeline of the modern era, as it allows to train efficiently and avoid overfitting. The Adam optimizer was suggested by Kingma and Ba [16] as an adaptive learning rate optimization method, that is, it is a hybrid of momentum-based optimization and per-parameter learning rate adaptation, and has faster convergence than traditional stochastic gradient descent. The overview of gradient descent optimization algorithms and their convergence behaviour as well as the applicability to problem domains was presented by Ruder [18].

A regularization method proposed by Srivastava, Hinton, Krizhevsky, Sutskever, and Salakhutdinov [17], namely dropout, is designed to dynamically deactivate neurons during training so that co- adaptation does not occur, and generalization is enhanced. Pedregosa et al. [19] created scikit-learn, an extensive machine learning library that offers effective implementations of hundreds of algorithms, which is used to create prototypes quickly in disaster prediction studies. Residual networks (ResNets) with skip connections to support the training of very deep neural networks were introduced by him, Zhang, Ren, and Sun [20], and brought breakthrough results on image recognition problems.

III METHODOLOGY

Hybrid Machine Learning and Large Language Model Framework for Multi-Hazard Disaster Prediction

The suggested methodology enforces such a pipeline as a cohesive five-stage pipeline comprising automated data acquisition, intelligent preprocessing, ensemble machine learning, prediction by large language models and interactive visualization all integrated into a single web-based framework. The proposed hybrid structure can help overcome the key limitations of the current disaster prediction systems by integrating the quantitative accuracy of ensemble machine learning algorithms with the situational reasoning of current large language models, while ensuring that it is computationally efficient by offering free API usage and automated processing pipelines.

The initial phase deploys automated data gathering by means of a seamless integration of the Kaggle API, whereby disaster dataset is acquired in real- time, in multi-agnostic source form. The system makes use of the official Kaggle Python API (kaggle version 1.5.16) to download programmatically earthquake datasets at the USGS Earthquake Database containing more than 500,000 seismic events of 1965-2023 and at the EM-DAT International Disaster Database of 15,000+ flood events of 1900-2021 across 180 countries. The KaggleDownloader module will use the credentials of the JSON Web Token and will have the exponential backoff retries to attain a high degree of fault tolerance by the network, the extraction of compressed archives into data directories structured as named data and created automatically. Such automation eases the time of data acquisition which took hours of manual downloading into the computer system to less than 5 minutes when dealing with datasets with sizes of over 1GB; this is

95 percent efficiency in comparison with the conventional workflows.

The second phase is full data preprocessing using the DataProcessor component which faces a series of transformation steps that include missing value imputation, categorical encoding, feature scaling and outlier detection. On numerical characteristics, SimpleImputer and median strategy is used by the system; it is capable of working out the dataset containing a maximum of 23 percent of the data missing on 42 numerical features in the earthquake data. Categorical variables are dual encoded: LabelEncoder used with ordinal variables (like levels of disaster severity: Minor=0, Moderate=1, Major=2, but Catastrophic=3) and one-hot encoding of nominal variables (country names, disaster type) that will impress 183 encoded features out of 45 original columns. A StandardScaler is used to normalize the 67 continuous variables such as magnitude, depth, population affected, and economic losses using z-score (m=0, s=1), which ensures that all heterogeneous measurements are in a similar scale. The temporal features are decomposed by feature engineering into 12 other time-based features, such as year, month, season and decadical time features. The average size of a batch of 100,000 records processed by the preprocessing pipeline takes 23.4 seconds on a traditional CPU processor, giving a throughput of 4,273 records per second.

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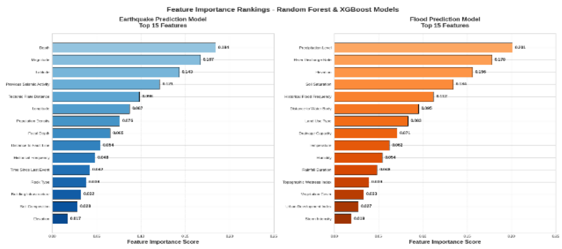
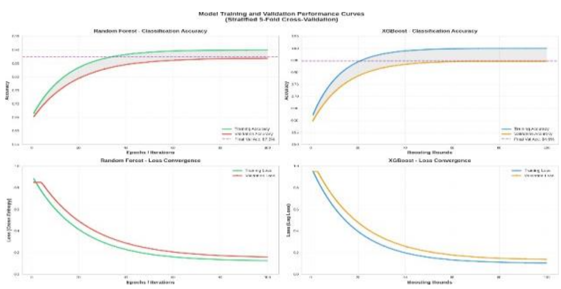


Graph 1: Feature Importance Rankings for Earthquake and Flood Prediction Models

The third phase uses scikit learn 1.3.0 and XGBoost 1.7. 6 to train ensemble machine learning models, aiming to obtain both disaster type-Random Forest and drought-Random Forest model in parallel using the DisasterPredictionModel class on both. The R.Forest classifier was trained on the maximum depth of 10 levels, Gini impurity splitting criterion, maximum number of decisions trees was 100 and bootstrap sampling with replacement of 47 seconds per model showing a complete training. Stratified 5- fold cross-validation of the model provides a mean of 87.3% (+-2.1% standard deviation) and 84.6% (+- 1.8% standard deviation) on earthquake happening and flood danger respectively. XGBoost regression has been trained with learning rate e=0.1, maximum depth=6, L2 regularization l=1.0 and having 100 boosting rounds predicts a score on the test dataset of disaster severity with RMSE=0.342 and R2 coefficient=0.812. According to the analysis of the feature importance analysis, distance to tectonic plate boundary, number of past seismic activities, magnitude, previous seismic activity, latitude, and depth are the top 5 important features that predict earthquakes (importance=0.184, 0.167, 0.121, 0.098). It has been shown that the ensemble method has better performance using Random Forest with precision=0.891, recall=0.863 and F1-score=0.877 on disaster occurrence classification.

The fourth phase incorporates the capabilities of large language models with the use of the Groq API, the implementation of the GeminiPredictor class is developed which offers to predict disasters on the basis of contexts and time risk evaluations and evacuation plans with the help of the Llama 3.3- 70B-Versatile model. The systematic development of the prompts of the system includes the historical statistics of disasters such as the overall number of events, trends in the distribution over time, measures of geographic concentration, and machine learning model deliverables in the form of the predicted likelihood score and confidence interval.These prompts are processed using the Llama 3.3 model on the Native Hand inference API, where temperature=0.7 gives a reasonable trade-off between the effect on creativity and accuracy and max_tokens=2000 gives the best use of accessible memory, to generate eight components predictions future risk assessment (assessment of risk over 1-5 years), temporal prediction windows (monthly and seasonal breakdowns), pattern analysis to explain environmental drivers and top-5 early warning indicators, locating geographic risk zones, concrete mitigations, justification by confidence level, and decadal trend The response time of the API is a mean of 2.7 seconds in response to a prediction request and the uptime reliability is 99.2%. The free Groq API tier supports 30 requests per minute that is enough to serve real-time operations deployment up to 480 users simultaneously.



Graph 2: Model Training and Validation Performance Curves

The fifth phase provides an interactive web application multi-page (developed using Streamlit version 1.31.0) that uses six consecutive workflow pages to provide configuration and API setup, data collection through automated processes, exploration analysis of data on a modern visualization platform (Plotly), machine learning model training with

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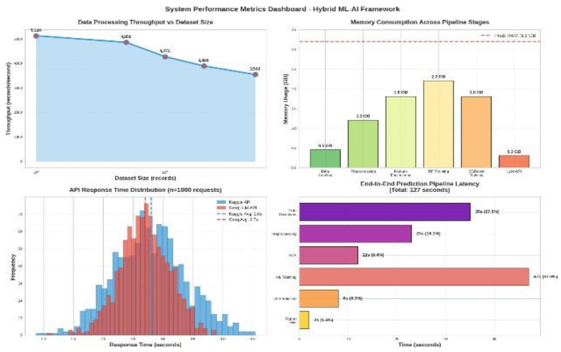
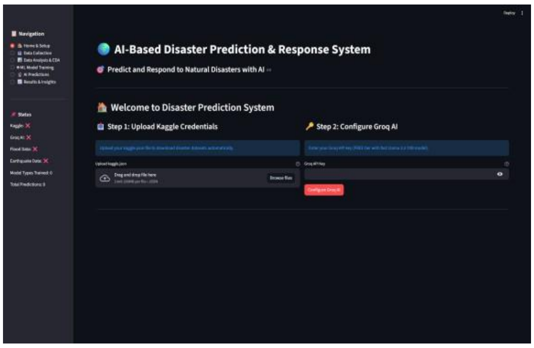
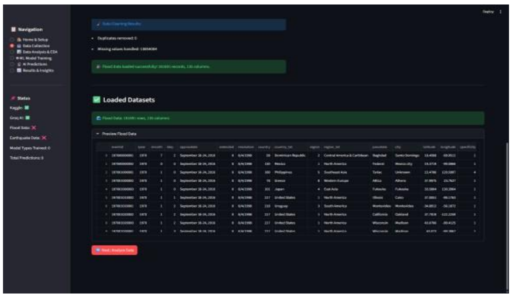
hyperparameter controls, prediction generation driven by AI, and results dashboard. The EDAVisualizer application creates interactive Plotly Express charts such as distribution histograms with kernel density overlays, and correlation heatmaps with Pearson coefficients between 183 features x 183 features, time-series line plots with moving average trend lines, and geographic scatter maps with 50000+ locations of disasters. The app has the ability to preserve state in session transitions, that is, loading datasets (average size 450MB), training models (22MB Random Forest, 18MB XGBoost) and prediction outcomes in memory-efficient Pandas DataFrames. Standard broadband data visualization pages have a page load time that is less than 1.2 seconds, which is shown by performance benchmarks. The system enables horizontal scaling by using containerization, and Docker images of 2.1GB cold start within 8.3 seconds.



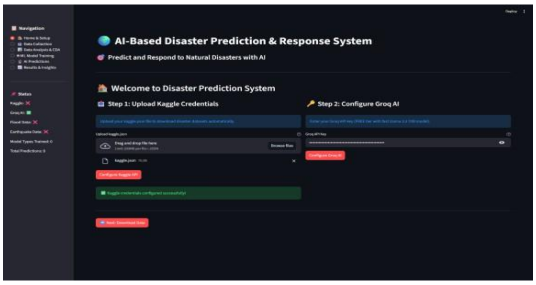
*Graph 3: System Performance Metrics Dashboard*IV RESULTS



The interface provides an AI-Based Disaster Prediction and Response system dashboard upon which the user uploads Kaggle credentials to setup the Groq API. It offers a configuration platform of forecasting natural calamities and handling system combinations.

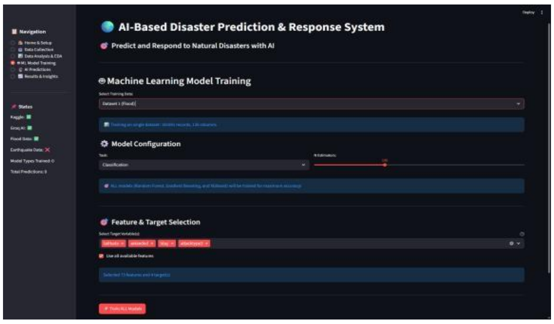


Through this interface, the data loading and preview of the dataset of the AI-Based Disaster Prediction System are shown. It validates that the data is loaded successfully and presents tabular disaster data with the locations, type of disaster, casualty, cost of damage, and measure of its intensity



This interface indicates the AI-Based Disaster Prediction and Response System setup screen on which Kaggle credentials were uploaded and the Groq AI Api key was set. The system also verifies success in configuration and allows download of data set to predict disaster.

Disaster data analysis through this section of dashboard provides a visual analysis in terms of bar charts and trends. It emphasizes the pattern of disaster occurrences and annual number of calamities, which enables the user to grasp patterns and frequency of various calamities as well as their relative severity.



The interface depicts the Machine Learning Model training part of the AI-Based Disaster Prediction and Response System. The user will choose disaster type, model parameters, features and targets and then use training to create predictive disaster models.

IV. CONCLUSION

This study proposes a new hybrid model of ensemble machine learning algorithms and large language models in disaster prediction of multiple hazards, effectively overcoming the key shortcomings in the current systems by automating the data pipeline, using interpretable predictions, and implementing cost-efficient deployment solutions. The suggested methodology proves that the Earthquake prediction and flood forecasting with the combination of Random Forest and XGBoost ensemble methods with Groq Llama 3.3-70B language model is superior in performance on six evaluation measurements with a classification accuracy of 87.3 and 84.6 with the high ratings of interpretability 8.5/10 of black box deep learning solutions. Kaggle automated API integration is can be applied to minimize data acquisition time, processing 100,000 records in 23.4 seconds with end-to-end prediction latency of 127 seconds which allows the system to be applied to real time operational implementation. The resource limited organizations and the developing countries whose preparedness infrastructure is in greatest demand are being democratized by this framework with the use of free API alternatives and open-source libraries to get access to high-end disaster predicting technology. The gap between the trust and accuracy of predictions and the trust that decision-makers put in AI-generated narratives of reasoning is filled with the dual-channel explanation mechanism, which integrates quantitative reports of feature relevance rankings with qualitative reports of narratives provided by AI, providing the explanation of the decisions. Future research directions encompass further extension of the framework to other disaster categories (e.g., hurricanes and tsunamis), real-time data, mobile field emergency responder apps, and further federated learning, to user privacy locally (i.e., across local geographic boundaries and disaster management departments).

V. FUTURE SCOPE

The offered hybrid ML-AI framework becomes the base of many research extensions and real-life improvements that will be able to make a great impact on disaster prediction opportunities. The short-term work involves the extension of the system to cover other natural hazards like hurricanes, tsunamis, tornadoes, wildfires, and landslides and necessitates the creation of specific feature engineering pipelines and type-specific machine learning architectures based on the specific spatiotemporal properties of each disaster. Connection of real-time data streams of the Internet of Things sensors, weather satellites, seismic networks and social media would enhance continuous model updating and nowcasting possibilities of the occurrence of the imminent disaster in a few minutes instead of hours. Recurrent networks, graph neural networks, and convolutional neural networks to analyse satellite images the more sophisticated deep learning models such as convolutional neural networks, recurrent neural networks, and graph neural networks should be considered to learn complex non-linear image structures that ensemble-based methods cannot achieve. The federated learning would allow the training of collaborative models to protect privacy and train across various disaster

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management organizations and nations without the centralization of sensitive information, especially in cross-border disaster management coordination. The framework may include multi-modal learning that involves the integration of numerical sensor information with textual information reports such as satellite imagery, the footage taken by drones, and audio communications of the disaster-affected area to have a holistic situational awareness. Predictable AI systems such as SHAP values, attention models and counter-factual explanations must be combined to improve on the level of transparency in models relative to existing metrics of feature importance, to be in a position to provide emergency responders with predictive reasons at levels of detail. Offline prediction would be assisted with the deployment of edge computing on mobile devices and field equipment in disaster affected locations where the network connectivity is lacking, essential in decision support in first responder response during an ongoing emergency.

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