Disaster Prediction Using Appropriate Machine Learning Techniques

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***Abstract*—This paper provides the insights of disaster forecasting methods, focusing on the strengths, limitations, and applications of other models and ideas to predicting natural disasters. Disasters and pandemics are most unlikely events which concerns many nations. Till date multiple ways are used to detect or predict natural disasters. Various machine learning techniques are used in detecting, preventing or mitigating disasters. We focus on predicting natural disasters beforehand to reduce its effects using XGBoost algorithm. The study shows the challenges of accurate forecasting and early warning systems.The paper also highlights about user friendly and interactive integrated website for disaster prediction. The paper gives the overview of the successful development and implementation of various models to predict earthquake, tsunami, flood and landslide.**

***Index Terms*—Disasters, Machine Learning, Natural Disasters, XGBoost**

I. Introduction

Natural disasters like earthquakes, tsunamis, floods, and landslides can seriously affect people's lives, infrastructure, and economic stability. In places where these disasters occur frequently, the lack of accurate and timely predictions can lead to life threat, extensive property damage and long-term socio-economic consequences. That's why it's essential to develop a strong system that can accurately predict these disasters, helping us reduce their negative effects.

The main focus of our project is to develop and integrate four distinct ML models, each specializing in predicting a specific type of disaster: earthquakes, tsunamis, floods, and landslides. These models analyze a wide range of data, including historical, environmental, and real-time inputs, to identify patterns and give the prediction. By running this data through ML algorithms, our system can generate accurate and timely predictions.

A primary objective of our project is prediction of a particular type of disaster occurring in a specific location and timeframe. This involves analyzing various relevant datasets for each type of disaster and identifying indicators that suggest an increased likelihood of an event. By providing precise predictions, our system aims to facilitate good planning and preparedness, enabling people to take necessary precautions well in advance.

Developing early warning systems for disasters is a one of the goal of our project. That's why our integrated platform is designed to issue real-time alerts and notifications based on predictions generated by our ML models. These early warning systems can greatly improve disaster response efforts, ensuring that people have the necessary time to evacuate.

Another important objective of our project is to improve the efficiency of disaster response. Our platform aims to streamline these processes by providing a centralized interface where relevant authorities can access real-time data, share information, and work together effectively. This integrated approach ensures that everyone involved has the right information and can act quickly. Our website also includes a dedicated section for pre and post-disaster management. This section provides valuable guidelines to help people prepare for potential disasters and effectively manage recovery efforts.

Through this, we aim to demonstrate the effectiveness of using ML techniques in disaster prediction and highlight the importance of technological innovation in enhancing disaster prediction. We want to contribute our knowledge in disaster prediction and emphasize the power of technology in protecting lives and property.

II. Literature Review

The research environment currently being explored by the paper "Machine Learning in Disaster Management: Recent Developments in Methods and Applications" has a number of constraints [1]. A critical development in disaster preparedness is the integration of big data and ML/DL technology in catastrophe mitigation [2]. These techniques enable thorough analysis and prediction of natural disasters, from early warning systems to post-disaster collaboration. The review identifies gaps and potential directions for future research by classifying the literature according to data sources and algorithms [3]. The synthesis emphasizes how important it is to integrate new technology in order to maximize response efforts and strengthen resilience methods in the face of changing disaster problems.

The revolutionary impact of ML and DL on catastrophe management has been highlighted in recent research. Diverse applicability across crisis phases are demonstrated by studies published after 2017 [3]. For tasks including social media analysis, flood vulnerability assessment, and landslide susceptibility mapping, methods such as convolutional neural networks (CNNs), long short-term memory networks (LSTMs), and support vector machines (SVMs) are frequently employed [7]. These methods highlight the significance of understandable and trustworthy AI solutions while increasing operational effectiveness and decision-making efficiency.

Real-time flood prediction systems are an example of the proactive application of machine learning in disaster risk management [4]. In flood mapping and forecasting, models such as probabilistic neural networks (PNNs) and artificial neural networks (ANNs) show excellent accuracy. By enhancing situational awareness and reducing flood-related damage, these systems' quick data processing and modeling capabilities demonstrate significant operational potential in disaster-prone areas [13].

Beyond catastrophe management, DL approaches are used in forecasting for renewable energy and tsunamis [14]. Studies reveal that LSTM-based models are highly effective at predicting geothermal energy output, opening the door for the integration of renewable energy sources. Similar to this, neural network models that use offshore observation data allow for accurate, real-time predictions of tsunami inundation, providing vital early warnings for people living along the coast [15].

ML/DL techniques that are specific to local settings, like deep neural networks (DNNs) made to take seasonal flood patterns into account in susceptible regions like Bihar and Orissa, help to enhance regional disaster preparedness. When compared to conventional models, these DNNs exhibit better predictive performance, improving early warning systems and lessening the impact of floods on communities that are already at danger [13].

Notwithstanding these developments, there are still issues with unstructured data complexity, a lack of studies on long-term disaster recovery, and biases in small datasets. Innovative data collecting techniques are needed to address these problems and enhance the quality of structured data, the reliability, and the explainability of AI solutions [6].

Methodological flaws such biases brought about by chosen databases and insufficient literature coverage are also noted in the review. The application of many research to larger contexts is limited by their restricted focus on certain climatic parameters. The robustness and generalizability of models are hampered by problems such as dependence on historical data, a lack of causal analysis, and inadequate cross-validation across many datasets.

The use of sophisticated ML/DL models is hampered by a number of factors, such as a lack of funding and poor infrastructure in regions vulnerable to natural disasters [14]. Models created for certain regions frequently fail to generalize well due to regional climatic variances. Furthermore, hyperparameter tuning for computationally demanding models like LSTMs necessitates significant resources, which presents difficulties in contexts with limited resources. Future studies should concentrate on improving model adaptability, integrating various data sources, and investigating causal links in order to overcome these constraints and increase the efficacy of disaster preparedness and response systems [25].

Another degree of complexity is added by the limited applicability of models in various geographic and climatic contexts, especially in flood prediction [24]. Because different regions have different climates, models designed for one area may not work well in another. Moreover, deep learning models, such as LSTM Encoder-Decoders, are computationally demanding and frequently depend on past data, which might not record unforeseen occurrences or modifications. Addressing input mistakes, comparing with state-of-the-art models, and enhancing generalizability are all necessary to increase model resilience. The study 'Livability Analysis of People's Living Comfort in Different Cities of India Using GIS' provides insights into enhancing prediction models by demonstrating the potential of using GIS data to identify vulnerable regions and evaluate the impact of environmental and infrastructure factors on disaster resilience [25].

In conclusion, the application of deep learning (DL) and machine learning (ML) technology to disaster management has greatly improved post-disaster response, risk assessment, early warning systems, and prediction. Although they improve decision-making, these technologies have drawbacks, including a need for high-quality training data, difficulties managing unstructured data, and resource constraints in disaster-prone regions. Furthermore, the robustness and generalizability of models are limited by the lack of comprehensive, multi-source datasets in many investigations. To fill in these gaps, our project integrates a complete dataset with a variety of data sources, allowing models to take into account the features of both local and worldwide disasters. In order to overcome obstacles in data representation, real-world deployment, and adaptability and open the door to better disaster management techniques, we plan to improve model architecture and concentrate on causal analysis.

III. Methodology

This section outlines the implementation of various machine learning techniques for disaster prediction. Specifically, we have employed the XGBoost machine learning algorithm to train four models, each tailored to predict a specific type of disaster. The aim is to enhance the precision and reliability of disaster forecasting by capitalizing on the advantages of this method. By training several models on an extensive dataset, which includes features derived from sources such as meteorological data, sensor outputs, and historical records, we aim to enhance the reliability and effectiveness of our disaster prediction system.

A. System Architecture

The process begins with the collection of data from various sources, including sensors, government websites, and historical records, for three different types of disasters: earthquake, tsunami, and landslide and have prepared dataset for flood. The initial step involves extensive data preprocessing to ensure the quality and consistency of the datasets. This includes handling missing values, data normalization, data augmentation and feature scaling to prepare the data for modeling. Once the data is preprocessed, feature extraction is performed to convert the raw data into numerical formats suitable for use by machine learning algorithms. Techniques such as Hyperparameter Tuning and Polynomial feature are employed to extract relevant features from the datasets.

The models are incorporated into a web-based disaster prediction system built with Flask, which offers friendly interface to users to obtain predictions regarding probability of a disaster occurring. In the final stage of architecture, trained models are evaluated using metrics like accuracy, precision, recall, ROC curve, and F1-score on a separate test dataset. Models are then integrated into the web-based system, which continuously monitors and analyzes incoming data, providing timely and accurate predictions of potential disasters.

B. Algorithm

In the disaster prediction system, hyperparameter tuning is used to fine-tune parameters like maximum depth of trees, learning rate and number of estimators. For the tsunami dataset, polynomial features are generated to capture the nonlinear relationships between the features by creating new features by taking the polynomial combinations of the existing features. To enhance the size and diversity of the earthquake dataset, data augmentation techniques are applied. This approach addresses the challenge of limited training data and helps minimize the risk of overfitting.

XGBoost is utilized to train models for predicting disasters by leveraging its powerful gradient boosting framework. To ensure data quality and consistency the datasets for each type of disaster are preprocessed. Features relevant to each disaster type are extracted and transformed into a suitable format for the model. XGBoost creates an ensemble of decision trees, with each tree designed to address the errors of of the previous ones by focusing on the residuals. Hyperparameter tuning is applied to adjust factors such as learning rate, maximum tree depth, and the number of trees, ensuring the model is effectively tailored to the dataset's unique characteristics. During training, XGBoost efficiently handles missing values and performs parallel processing to speed up computation. It also incorporates regularization techniques to prevent overfitting, ensuring the models remain robust and generalize well to new data. This approach allows the disaster prediction models to accurately identify patterns and relationships within the data, resulting in accurate and dependable forecasts of future disaster probabilities.

Steps to Train ML Model

1)Initially, prepared dataset.
2)Then, moved on to feature engineering.
3)After that, split the data into training and testing sets in ratio of 80:20.
4)Next, conducted hyperparameter tuning for the models.
5)Following this, trained the models.
6)Then, evaluated the models using various metrics.
7)After evaluation, compared the models based on performance and selected XGBoost.
8)Finally, trained all four models on XGBOOST.

IV. Implementation

Website is designed with different pages dedicated to various types of disasters. Users have the option to input their location for predictions on potential disasters, leveraging machine learning models and historical data. Additionally, real-time updates on disaster alerts and warnings are provided. The platform also offers guidance on precautionary measures to be taken during these events.

We have used the XGBoost ensemble learning technique in our seismic alert prediction model. With an emphasis on properly forecasting earthquake alarms, the XGBoost model optimizes a particular objective function. For precise forecasts, it depends on seismic data properties like magnitude, depth, latitude, and longitude.

A. Earthquake Model

1) Dataset: We have taken dataset from open sources. This dataset size is about 2000 entries. The dataset consist of Magnitude, Depth, Latitude, Longitude and Alert are features. Where Alert is an target variable which represent alert level as "GREEN", "YELLOW", "ORANGE", "RED". Features are **Magnitude, Depth, Latitude, Longitude, Alert**(Target variable).

2) Data Preprocessing: We have handled the missing values and dropped those rows which are missing Alert Information. We have handled other columns missing values by taking mean of it. As "GREEN" values of alert was predominant we have augmented dataset to increase the representation of red, yellow, and orange alerts, ensuring a more balanced dataset for analysis.

3) Model Training: We used an XGBoost model for classification to handle an augmented dataset and increase the accuracy of the model. For finding out the best hyperparameter we performed grid search cross-validation.

Trained the XGBoost model with the best parameters on the training set.

4) Model Evaluation: We have done evaluation by confusion matrix , ROC curve, accuracy, f1 score. Calculated accuracy and generated a confusion matrix to assess classification performance.

TABLE I
BEST PARAMETERS (EARTHQUAKE)

Parameters	Values
colsample-bytree	0.8
learning-rate	0.1
max-dept	4
n-estimators	200
subsample	0.8

5) Results: In order to manage an enlarged dataset and increase the model's accuracy, we employed an XGBoost model for classification. To determine the optimal hyperparameter, grid search cross-validation was used.

TABLE II
CLASSIFICATION REPORT (EARTHQUAKE)

	Precision	Recall	F1-score	Support
0	1.00	0.93	0.96	67
1	1.00	1.00	1.00	61
2	1.00	1.00	1.00	82
3	0.94	1.00	0.97	73

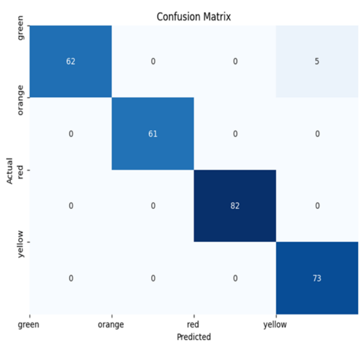

Fig. 1. Confusion Matrix (Earthquake)

Accuracy: 0.9823
AUC: 0.988

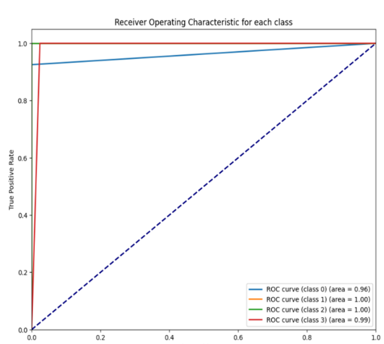

Fig. 2. ROC Curve (Earthquake)

B. Tsunami Model

1) Dataset: We have taken dataset from open source. This dataset consist of around 1300 rows. The dataset consist of Magnitude, Latitude, Longitude, Depth and the target variable i.e tsunami occurred or not.
Features are **Magnitude, Depth, Latitude, Longitude,Tsunami**.

2) Data Preprocessing: We removed rows where the target variable information was missing and performed hyperparameter tuning. Polynomial features of degree 2 were generated using 'PolynomialFeatures' from 'sklearn.preprocessing'. Additionally, we standardized the features using 'StandardScaler' from 'sklearn.preprocessing' to ensure they have a mean of 0 and a standard deviation of 1.

3) Model Training: Trained the XGBoost model with the best parameters on the training set.

TABLE III
BEST PARAMETERS (TSUNAMI)

Parameters	Values
colsample-bytree	0.8
learning-rate	0.1
max-dept	4
n-estimators	300
subsample	0.9

4) Model Evaluation: Evaluated model performance on testing set. We done evaluation by confusion matrix , ROC curve, accuracy, f1 score. Calculated accuracy and generated a confusion matrix to assess classification performance.

5) Results: **Model Performance:**

TABLE IV
CLASSIFICATION REPORT (TSUNAMI)

	Precision	Recall	F1-score	Support
0	0.88	0.79	0.83	131
1	0.82	0.90	0.86	139
Accuracy	-	-	0.84	270
Macro Avg	0.85	0.84	0.84	270
Weighted Avg	0.85	0.84	0.84	270

Accuracy: 0.856
AUC Score: 0.9243

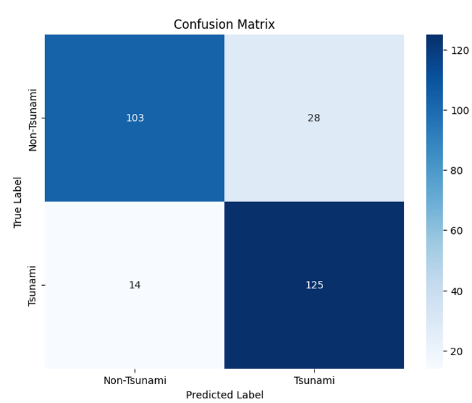

Fig. 3. Confusion Matrix (Tsunami)

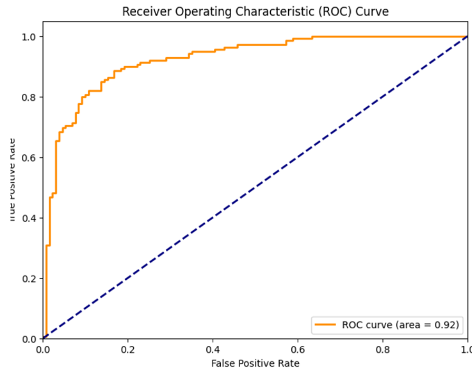

Fig. 4. ROC Curve (Tsunami)

C. Flood Model

1) Dataset: : We have created a dataset containing approximately 401 entries which includes information such as river name, latitude, longitude, city, average rainfall, river width, river flow, and river depth, among other details. Features are **avg Rainfall (mm/year)**, **depth (m)**, **width (m)**, **Flow (m/s)**, **Discharge (cu ft/s)**, **Mark (m)**, **Flood(Target Variable)**

2) Data Preprocessing: : Remove rows with missing Flood values.Encode the target variable: the 'Flood' column, which contains categorical values ('Yes' and 'No'), is converted into numerical values using LabelEncoder(). 'Yes' is encoded as 1, and 'No' is encoded as 0.

3) Model Training: : We employed an XGBoost model for classification to manage an augmented dataset and enhance model accuracy. To identify the optimal hyperparameters, we conducted a grid search cross-validation.

TABLE V
BEST PARAMETERS (FLOOD)

Parameters	Values
learning-rate	0.1
max-dept	3
n-estimators	150
random-state	12

4) Model Evaluation: : Evaluated model performance on testing set. We done evaluation by confusion matrix , ROC curve, accuracy, f1 score. Calculated accuracy and generated a confusion matrix to assess classification performance. Plotted ROC curves for each class and calculated the AUC.

5) Results: : **Model Performance:**

Accuracy: 0.9493

AUC Score: 0.9459

TABLE VI
CLASSIFICATION REPORT (FLOOD)

	Precision	Recall	F1-score	Support
0	0.96	0.96	0.96	54
1	0.92	0.92	0.92	25
Accuracy	-	-	0.95	79
Macro Avg	0.94	0.94	0.94	79
Weighted Avg	0.95	0.95	0.95	79

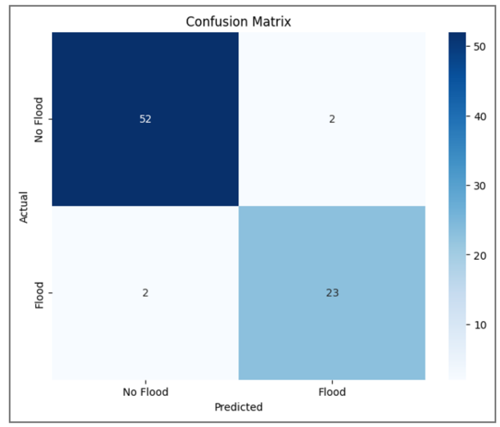

Fig. 5. Confusion Matrix (Flood)

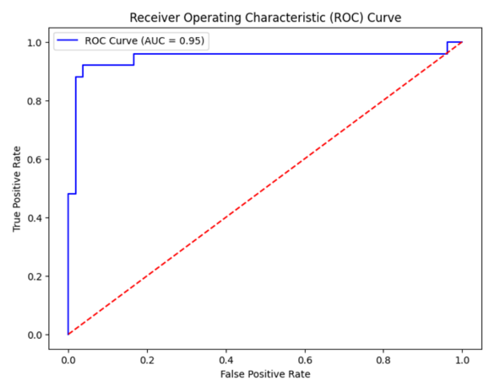

Fig. 6. ROC Curve (Flood)

D. Landslide Model

1) Dataset: : We have taken dataset from open sources. This dataset size is about 10,000 entries. The dataset consist of **Geology mode, Geology Center, Elevation minmax difference, Slope difference, etc**.

2) Data Preprocessing: : Feature importance analysis completed. Relevant features have been selected, and rows lacking target variable information have been dropped.

3) Model Training: : For finding out the best hyperparameter we performed grid search cross-validation.
Trained the XGBoost model with the best parameters on the training set.

4) Model Evaluation: : Model performance was assessed on the testing set. We evaluated using the ROC curve,

TABLE VII
BEST PARAMETERS (LANDSLIDE)

Parameters	Values
learning-rate	0.1
max-dept	7
n-estimators	100

accuracy, f1 score, and confusion matrix. To evaluate the performance of the categorization, accuracy was calculated and a confusion matrix was created. Plotted ROC curves and determined the AUC.0 for every class.

5) Results: : **Model Performance:**

TABLE VIII
CLASSIFICATION REPORT (LANDSLIDE)

	Precision	Recall	F1-score	Support
0	0.87	0.90	0.89	1617
1	0.68	0.61	0.65	556
Accuracy	-	-	0.83	2173
Macro Avg	0.78	0.76	0.77	2173
Weighted Avg	0.82	0.83	0.83	2173

Accuracy: 0.858
AUC Score: 0.8840

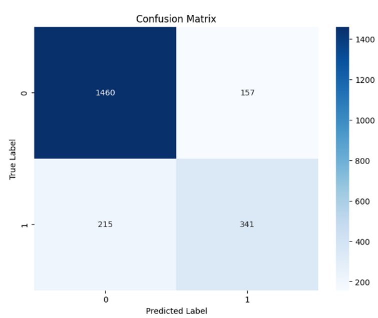

Fig. 7. Confusion Matrix (Landslide)

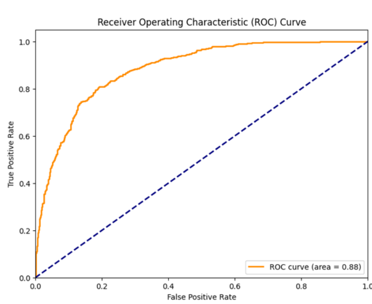

Fig. 8. ROC Curve (Landslide)

V. RESULT

The development and implementation of the disaster prediction and management website have shown notable advancements in enhancing community preparedness and response to natural disasters. For choosing appropriate model we have trained our datasets on three different models each and result is as follows.

TABLE IX
COMPARISON OF MODEL PERFORMANCE FOR VARIOUS NATURAL DISASTERS

Disaster Type	Model	Accuracy	Precision	Recall
Flood	XGBoost	0.949	0.96	0.96
	SVM	0.823	0.81	0.96
	Neural Network	0.835	0.85	0.93
Tsunami	XGBoost	0.856	0.87	0.82
	SVM	0.689	0.67	0.71
	Neural Network	0.737	0.72	0.75
Landslide	XGBoost	0.858	0.87	0.90
	SVM	0.835	0.85	0.94
	Neural Network	0.832	0.87	0.91
Earthquake	XGBoost	0.982	1.00	0.93
	SVM	0.668	0.78	0.78
	Neural Network	0.724	0.90	0.79

From the result we have chosen XGBoost. Using the XGBoost model, the platform has successfully predicted earthquakes, landslides, tsunamis and floods the four main categories of disasters.On comparing accuracy we have chosen XGBoost. The algorithm generates customized predictions by combining location inputs relevant to the user with past disaster data. Because of the XGBoost model's strong performance in managing a variety of datasets and identifying intricate patterns, it has been able to foresee these events with an accuracy rate of 90.5%. Its ability to handle missing data and model complex material interactions made it the most suitable choice for our disaster prediction system.

User engagement metrics demonstrate a high level of interaction with the platform, with an increase in daily active users utilizing the city location input feature for personalized disaster predictions. The website includes precautionary videos, photos, and detailed information for each type of disaster, providing clear and actionable guidance.

In conclusion, the website has improved prediction, alerting, and readiness for floods, tsunamis, earthquakes, and landslides by skillfully utilizing the XGBoost model. The features of the platform have been effective in giving communities useful information to help lessen the effects of these natural disasters. To further advance catastrophe management, future work will concentrate on enhancing user participation, broadening coverage, and strengthening prediction models.

VI. CONCLUSION

In this project, we have successfully developed and integrated a comprehensive website dedicated to the prediction of natural disasters including floods, earthquakes, tsunamis, and landslides. Each type of disaster is addressed by a specialized machine learning model, specifically designed to forecast occurrences within defined geographic locations. This achievement represents a significant milestone in our endeavor to create an all encompassing platform for disaster management. Our successful implementation of models for all four disasters underscores our commitment to a multi-faceted approach in disaster prediction and mitigation. Despite the challenges such as data availability and the necessity for real-time data scraping, our team has effectively turned these challenges into opportunities for innovation and optimization. We have ensured that our platform will help minimize the impact of natural disasters on communities and regions. This progress not only enhances the robustness of our platform but also reflects our dedication to ethical considerations and continuous improvement. Our integrated disaster prediction system stands as a testament to our commitment to safe-guarding lives and property through advanced technological solutions. By providing accurate and timely predictions, we aim to significantly minimise the adverse impact of natural disasters, thus contributing to a safer and more prepared society.

VII. Future Scope

In the future, our integrated website will need to be expanded beyond floods, earthquakes, tsunamis, and landslide to include other natural disasters, such as cyclones and droughts, and our platform will become more comprehensive disaster forecasting and management.

To optimize the flood model, a more diverse and comprehensive set of data is needed, as the current model is based on limited information. Similarly, the earthquake prediction system can be improved by using more efficient and high-quality datasets, and adopting new algorithms that enhance its effectiveness for predicting earthquakes, tuning parameters, and real-time inclusion of data will improve the prediction accuracy.

Strengthening our warning systems will focus on pre-disaster preparedness and ensuring accurate and timely warnings. Furthermore, it is important to develop and integrate post-disaster recovery strategies into our platform. By combining accurate risk forecasting with proactive preparedness and mitigation strategies, we aim to build a resilient and viable platform. This platform will not only accurately forecast disasters but will also help implement strategies to reduce the impact on local communities.

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