Hybrid Stacking Model for Earthquake Magnitude Prediction in Japan Using Time Series Data (1970-2024)

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Abstract: Seismic prognosis is considered as one of the most important scientific challenges. Among many nations, Japan is in greatest need of such system due to the constant and frequent occurrence of strong earthquakes caused by tectonic activity in the Pacific seismic zone. Therefore, the development of an advanced early warning system is necessary to predict the earthquake in advance to prevent the disaster. For this purpose, data related to earthquakes are collected from 1970 to 2024. This time-series data is trained using the hybrid stacking model, based on Random Forest, Extra Trees and CatBoost as base models and Linear Regression as a meta-model. The objective of the proposed model is to enhance the precision of earthquake magnitude forecasting, focusing on significant earthquakes. The performance of the proposed model is evaluated using two parameters i.e. R-Squared and Mean Square Error (MSE). The dataset is split in to 80:20 ratio for training and testing data respectively. From the results, it is inferred that the developed hybrid model decreases error rates with an R-squared value of 0.83 and MSE of 0.066. Thus, the proposed work helps to improve early warning systems for earthquakes, minimizing risks in Japan.

1 INTRODUCTION

Japan situated at the intersection of four tectonic plates (Pacific, Philippine Sea, Eurasian and others) is one of the most seismic-sensitive countries. The country has suffered from some of the worst catastrophic earthquakes in history. They are the Great Kanto Earthquake (1923), which claimed more than 100,000 lives and the Tohoku Earthquake (2011), which resulted in extensive destruction of buildings and important infrastructure, such as Fukushima nuclear reactor complex. These two quakes highlight the fact that the world still requires better and more efficient means of predicting earthquakes in order to reduce the effects of future ones.

Elastic movements in Japan are mainly caused by the Benioff zones, where the Pacific Plate is being pushed below both the Philippine Sea Plate and the Eurasian Plate. This tectonic activity makes this area highly susceptible to various types of earthquakes such as megathrust earthquakes at the subduction interface. While advancements have been made in seismic monitoring and early warning systems, accurate prediction of time, location and magnitude of earthquakes still remains challenging. This is due to their unpredictable and flexible nature. Among the existing earthquake forecasting techniques, Seismic Gap Theory and Historical seismicity have made significant efforts to forecast earthquakes. However, these approaches have not been successful in regions with complex tectonic activities like those in Japan.

So, in this work to overcome the limitations, hybrid stacking model is used to predict the magnitude of Earthquakes. The models such as Random Forest Regressor, Extra Trees Regressor and CatBoost Regressor are used as the first-level models, while a Linear Regression model is employed as the second-level model in the stacking approach. For this, time series data of Japan is collected from 1970 to 2024. The collected data is split into 80% for training and the remaining 20% for testing. This approach aims to improve the prediction of earthquake magnitudes and enhance the understanding of how to improve early warning systems in Japan. This extends the existing work by integrating various Machine

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Learning models to hybrid models to improve the potential for more accurate seismic forecasting.

The rest of the paper is organised as follows: Section-II presents the Literature Review, Section-III explains the proposed methodology, Section-IV discusses the results and its comparison, Section-V concludes the paper and outlines the Future work.

2 LITERATURE REVIEW

In (Joshi et al., 2023), the authors have outlined the disadvantages of the classical form of early warning systems. According to the authors, the disadvantage is that the system provided delayed response. This is due to the time required for data analysis from several stations. In this paper, the authors have focused particularly on the ability of ML models to improve the predictive capabilities based on the multi-parametric relationships within the collected data. Feature engineering is also applied in this study resulting in 29 features derived from the initial phase of the P wave in relation to earthquake magnitude. From the results, it is inferred that XGBoost model effectively enhanced the performance by giving better prediction results, for which the average error is lower than conventional methods. In this paper (Asim et al., 2017), authors focused on the analysis of earthquake magnitude prediction for the Hindukush region through a ML classifier based on historical data of past seismicity. Eight physical characteristics in accordance with geophysical concepts were used to simulate future earthquakes, specifically those exceeding a magnitude of shake of 5.5. The authors have used various ML methods and evaluated the performance of the models using sensitivity and accuracy.

The XGBoost-SC model for ground motion prediction was developed in this paper (Dang et al., 2024) using 67,164 data records of shallow crustal earthquakes that occurred in Japan between 1997 and 2019. Some of the features include magnitude, depth, Vs30, hypo-central distance, altitude, and focal mechanism. From the results, it is inferred that XGBoost has shown to be more successful and outperformed traditional approaches in terms of accuracy and stability. The result of the SHAP analysis confirmed the importance of features and demonstrated the model's overall value in predicting future disaster engineering, particularly with regard to earthquakes. The primary objective of this paper (Dutta et al., 2011) is to develop a standard earthquake database for the South Asian region (1905–2009) in the context of comparing seismic risks in low-to-moderate seismicity regions. Specifically, the accuracy of the magnitudes greater than five was improved using linear regression to model the relationship between earthquake magnitude, latitude, longitude and depth. Weka had better performance than SPSS in the prediction of earthquake magnitude when data was smoothed. The results suggested that WEKA is more suitable for this task.

In this work (Ahmed et al., 2024), several ML techniques were applied on data obtained from the US Geological Survey to classify earthquake magnitudes. During data pre-processing, it was found that more than 10 percent of the data has NULL values. Suitable actions such as imputation and removal of “null” feature were taken. To improve the performance of the model, features were encoded ‘one hot’ and feature scaling was applied. With the better hyperparameters, the SVM model achieved the most accurate results, with MSE of 0.10 and a coefficient determination of 0.93. In a recent study, the effects of earthquakes, including ground movement and economic losses were examined. The Researchers have used a global dataset and shaped the same using a technique called gradient boosting regressor to forecast earthquake events with respect to date, time and magnitude. They broke down the predictions into smaller components and the results were improved to 86.1% for magnitude and 99.7% for depth, which actually surpassed previous models.

In (Wang & Wang, 2024), the authors have also tried to determine risk-free zones to minimize loss by comparing actual and predicted values. In (Sadhukhan et al., 2023) , the authors have explored the use of DL algorithms for earthquake prediction, focusing on significant seismic magnitudes from regions such as Japan, Indonesia and Hindu-Kush Karakoram Himalayan (HKKH) area. Three DNN models such as LSTM, Bidirectional LSTM and Transformer were used to analyze the correlations between the seismic features and possible earthquake activities. For Japan dataset, LSTM outperformed all the other models, while Bi-LSTM outperformed all other models for the Indonesia region and the transformer model outperformed all other models for the HKKH region. The models gave good results for predicting earthquake magnitude in the range of 3.5 to 6.0. Various studies have focused on improving earthquake prediction using ML models. The limitations of the existing systems are:

- traditional system suffer from delayed response

- current model still face challenges in achieving accurate prediction and less error rate.

3 PROPOSED METHODOLOGY

In the proposed work, the dataset is cleaned by handling missing values and removing unnecessary columns. The categorical features are labelled using one-hot encoding. Further, the dataset is split into 80% for training and the remaining 20% for testing. The data is then fed to base model and the output of it is given to meta model as shown in Fig.1.

3.1 Dataset Pre-processing

The dataset consists of earthquake data from Japan taken from the USGS, with 25,326 rows and 27 columns. After cleaning the data by removing unnecessary columns ('id', 'updated', and 'place'), categorical columns ('magType', 'net', 'type', 'status', 'locationSource', and 'magSource') were encoded using LabelEncoder. Label encoding is applied to convert categorical data into numerical values, making it compatible with ML models for processing. The dataset pre-processing for the collected data is done as follows:

- *Removing Unnecessary Columns:* Columns such as 'id', 'updated' and 'place' were removed because they may not provide relevant information for prediction. For example, 'id' is a unique identifier and does not contribute predictive value.
- *Label Encoding:* Categorical columns were converted into numerical representations using LabelEncoder. This is essential for models like Random Forest and XGBoost that work with numerical data. For instance, 'magType' may have values like 'mb', 'ms', etc., which are transformed into numbers.
- *Features:* The cleaned data focuses on numerical features like 'latitude', 'longitude', 'depth', 'mag', 'nst', and 'rms', along with categorical ones like 'magType'.

3.2 Base Models

The pre-processed dataset is split into 80 % for training data and the remaining 20% for testing data. The pre-processed data is given as input to the base models. The base models are

3.2.1 Random Forest Regressor

The Random Forest Regressor is an ensemble model in ML that creates several decision trees while training and then delivers the averaged results. It builds on the method bootstrap aggregation were each tree is learnt from a boot strap sample of the data.

During the splits in the trees, the candidate features to be used for splitting are chosen randomly so as to avoid proximity between individual trees and enhance the generalization power of the entire system. Random Forest outperforms single decision trees when it comes to minimizing overfitting, and it is exceptionally apt for regression problems as well as classification (Al Banna et al., 2021). The model is capable of analysing non-linear relationship in the data; and since the output is an aggregation of many trees it is less sensitive to noise in the data. In mathematical terms, the prediction of a Random Forest model is expressed as in Equation (1).

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} f_t(x) \quad (1)$$

where T is the total number of trees in the forest and $f_t(x)$ is the prediction made by the t^{th} tree for a given input x. Each decision tree in the forest is built by recursively splitting the data based on certain features, chosen to minimize a loss function, typically the mean squared error (MSE) for regression tasks. The model continues splitting the nodes of each tree until a stopping criterion, such as a maximum depth or a minimum number of samples per leaf, is met. Random forest identifies non-linear patterns and address issues regarding variance through accumulation of outcome from a variety of classifier trees. The bootstrapping mechanism assures the existence of stability in the predictions even if there is a high level of noises.

3.2.2 Extra Trees Regressor

Extra Trees Regressor (Extremely Randomized Trees) is an ML algorithm that involves several decision trees created randomly. In Extra Trees, the splitting nodes that fractures at each node is randomly chosen within a given range other than being chosen at best split based on certain criterion such as the mean squared error (Kumar et al., 2023).

This randomness both in the feature and in the split selection also helps to lessen the variance of the model and therefore generalizes well and does not over fit. Extra Trees enhance the accuracies' homogenization and generation speed in addition to general stability by averaging the output of several trees randomly constructed. Random split in Extra Trees improves generality and resolves the overfitting problem. It gives variance by aggregating the results of an extremely randomized decision trees model.

3.2.3 CatBoost Regressor

CatBoost Regressor is actually a gradient boosting model that is excellent when used with datasets that contain both categorical and numerical variables (Jozinović et al., 2022).

The key difference between the CatBoost model and the other models is that while the gradient boosting is used, ordered boosting is applied, which helps to minimise the target leakage problem and to prevent overfitting, which is characteristic of small datasets (Mir et al., 2022).

The model continuous features are engineered using "target statistics", where a value is given to a continuous variable based on the distribution of the target variable by the categories of the dummy variable (Kalavakunta & Parthipan, 2024). This ordered boosting technique helps in preventing the model to overlearn the training data as in the normal boosting techniques of using part of the data set for prediction in boosting. Therefore, CatBoost works well with density data and offers stable performance irrespective of significant feature transformation. The prediction in CatBoost is calculated sequentially according to the gradient boosting algorithm, when new trees try to reduce the residual error of previous predictions (Su & Zhang, 2020). The prediction at iteration t is given by Equation (2)

$$\hat{y}^{(t)} = \hat{y}^{(t-1)} + \eta \cdot g^{(t)}(x) \tag{2}$$

where η is the learning rate, $g^{(t)}(x)$ is the prediction from the new tree at iteration t and $\hat{y}^{(t-1)}$is the prediction from the previous iteration.

In CatBoost, the model iteratively refines its predictions by focusing on errors from previous iterations, combining the strengths of boosting with advanced handling of categorical data for superior performance. This model adds a gradient-boosting perspective to the stacking approach, complementing the randomness of Random Forest and Extra Trees models. Its ability to handle categorical features natively provides an advantage when modeling seismic data, which often includes discrete categories. CatBoost ensures stable performance irrespective of the nature of the dataset (dense, sparse, or mixed).

3.3 Meta Model (Linear Regression)

Linear regression is a fundamental method of using statistics in developing the relationship between one or more variables. The advantages of this model are simplicity, interpretability and strong predictive performance on input features. The primary objective of this model is to find a line that predicted values (Varshney et al., 2023). This approach provides a model that assumes a direct linear relationship, minimises the deviations between the actual and the allowing for clear inference on how changes in predictor variables influence the outcome.

In the proposed hybrid stacking approach for earthquake magnitude prediction, the Linear Regression model serves as the meta-model, combining the predictions from the base models such as RF, ET and CatBoost. Instead of using the predictions from these models directly, the Linear Regression model treats them as features, optimising the strengths of each algorithm (Roy et al., 2024). This result in more accurate and reliable final predictions compared to the case with each individual model. This hybrid approach not only increases prediction but also provides insights into how each base model contributes to the final result, which is particularly valuable in applications such as in disaster response and earthquake vulnerability.

The mathematical formulation of the prediction in a Linear Regression model is expressed in Equation (3)

$$\hat{y} = \beta_0 + \sum_{j=1}^{n} \beta_j x_j \tag{3}$$

where $\hat{y}$ represents the predicted earthquake magnitude, β_0 is the intercept, β_j are the coefficients for each predictor x_j (indicating the predictions from the base models), and n is the total number of base models (Katole et al., 2024).

The model coefficients are determined by minimizing the Residual Sum of Squares (RSS), defined as in Equation (4)

$$RSS = \sum_{i=1}^{m} (y_i - \hat{y}_i)^2 \tag{4}$$

where y_i is the actual target value and $\hat{y}_i$ is the predicted value. Through this method, the stacking approach effectively integrates the capabilities of various models, ultimately leading to improved predictions in earthquake magnitude forecasting.

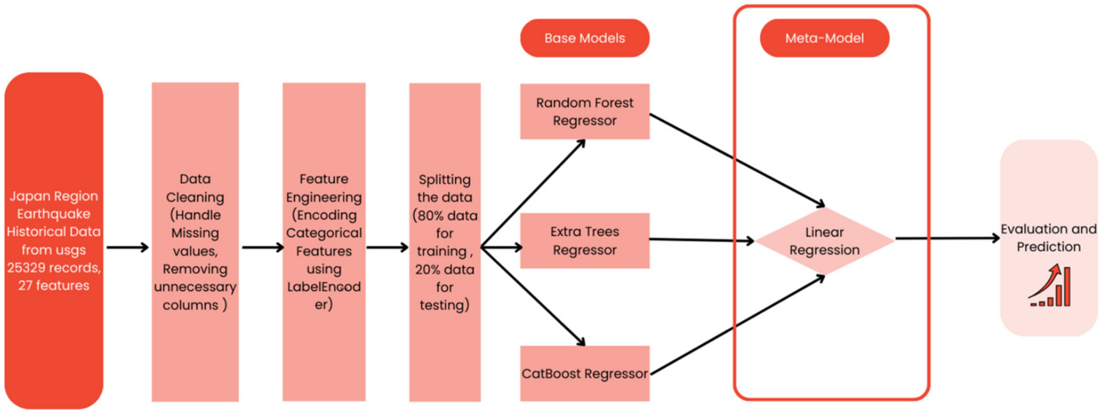

Figure 1. Architecture of Proposed Methodology

Linear Regression determines weights of the base models and comes up with the best weights that complements each others strengths. The passthrough mechanism helps Linear Regression to benefit from the forecasts produced by base models and the residual distribution in original features. The coefficients of Linear Regression also allow for interpreting directly the contribution of each base model and original feature to the stacking framework. Linear Regression does not require many computations making it more appropriate for large data sets or a situation where, an over-speed meta-model training is required.

4 RESULTS AND DISCUSSION

4.1 Evaluation Metrics

In evaluating earthquake prediction models, various performance metrics are employed to assess the accuracy and reliability of predictions. These metrics include Mean Squared Error (MSE), R-squared (R^2), Root Mean Squared Error (RMSE), and so on. Each of which provides distinct insights into model performance.

4.1.1 Mean Squared Error (MSE)

MSE measures the average squared difference between actual and predicted values, offering a penalization for larger errors. A lower MSE value indicates better predictive accuracy as in Equation (5)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{5}$$

where y_i represents the actual value, $\hat{y}_i$ the predicted value, and n is the total number of predictions.

4.1.2 R-squared (R^2)

R-squared Evaluates the proportion of variance in the target variable explained by the model. It ranges from 0 to 1, with higher values signifying better model fit as in Equation (6)

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{6}$$

where $\bar{y}$ is the mean of actual values.

4.1.3 Root Mean Squared Error (RMSE),

RMSE a derivation of MSE, is the square root of MSE. It retains the same scale as the target variable, making it easier to interpret as in Equation (7)

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{7}$$

4.1.4 Mean Absolute Error (MAE)

MAE calculates the average magnitude of prediction errors, without considering their direction. It is less sensitive to outliers compared to MSE or RMSE is shown as in Equation (8)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{8}$$

4.1.5 Mean Absolute Percentage Error (MAPE)

MAPE quantifies prediction error as a percentage, offering scale-independent insight. Its formula is shown as in Equation (9)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \widehat{y_i}| \times 100 \qquad (9)$$

Together, these metrics provide a complete evaluation of the accuracy of earthquake prediction models. They highlight both prediction rate and the error patterns to choose the model for prediction.

4.2 Experimental Results

In this paper, ML models such as XG Boost, Random Forest, Gradient Boosting, Lasso, Ridge, SVM, KNN, ElasticNet, Extra Trees and CatBoost are compared and the results are presented in Table 1.

The actual earthquake magnitudes and those expected based on the stacking model were also compared as a way of testing the validity of the model. The actual values the magnitudes are shown as a blue/gray continuous curve, while the predicted values are shown by the orange dashed line in Figure 2. The proximity of the two lines further supports the fact that the stacking model can replicate actual seismic data. There is a lack of variability, but this is perfect for illustrating the ability of a model to analyze the change in magnitude.

In addition to the gradient coloring, the heatmap is also presented in Figure 3 for assessing the values of each metric to that of the line plot.

By evaluating the models using MSE, RMSE, MAE, MAPE and R-squared, the lower coefficients and a higher R-squared value indicate better model performance. Among these models tested with the considered datasets, the stacking model provided the least error estimations and the highest R^2 (0.832) confirming its efficiency and high predictive abilities as shown in in Figure 3.

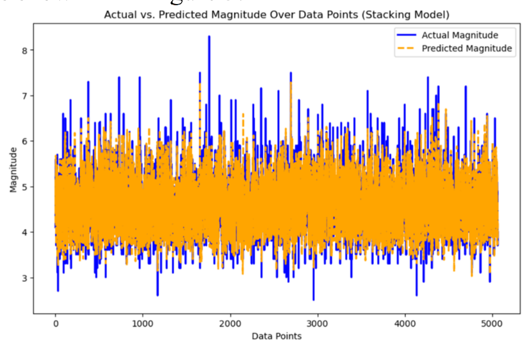

Figure 2: Actual vs Predicted Magnitude prediction using Proposed Method

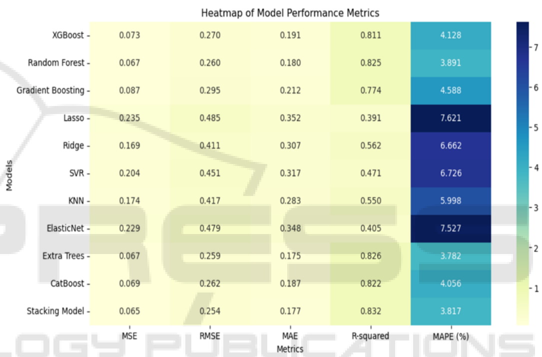

Figure 3: Heatmap of Model Performance Metrics

The overall model comparison across Metrics is shown in the Figure 4.

Table 1. Comparison of the performance of models

MODELS	MSE	RMSE	MAE	R-squared	MAPE(%)
XGBoost	0.0727	0.2697	0.1910	0.8112	4.1281
Random Forest	0.0674	0.2596	0.1801	0.8251	3.8912
Gradient Boosting	0.0870	0.2949	0.2121	0.7743	4.5875
Lasso	0.2348	0.4845	0.3522	0.3909	7.6209
Ridge	0.1689	0.4110	0.3067	0.5618	6.6623
SVR	0.2038	0.4514	0.3166	0.4712	6.7261
KNN	0.1735	0.4166	0.2826	0.5497	5.9979
ElasticNet	0.2292	0.4787	0.3480	0.4053	7.5265
Extra Trees	0.0669	0.2587	0.1749	0.8263	3.7788
CatBoost	0.0685	0.2617	0.1873	0.8222	4.0561
Stacking Model	0.0648	0.2545	0.1768	0.8319	3.8219

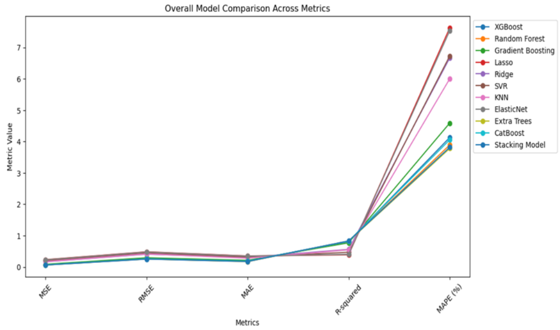

Figure 4. Overall Model Comparison Across Metrics

In the confusion matrix as shown in Figure 5, results of the stacking model shows how well it predicts the earthquake magnitude for various ranges. The model shows high accuracy in the range between 2-4, where 3,919 instances were forecasted correctly, therefore its capability in handling the most frequently recurrent range of magnitude as shown in the dataset. The experiments of the 0-2 range of estimates had 823 correct and 172 wrong classifications with the 2-4 range. The misclassification is very low in the higher magnitude zones suggesting that the model has a bias towards lower and mid-range magnitudes. This distribution means that although the stacking model is precise for relative low and about average magnitude seismic events, the quality of this work revealed that the possibility exists to improve the accuracy of the stacking model for more rare, higher magnitude earthquakes.

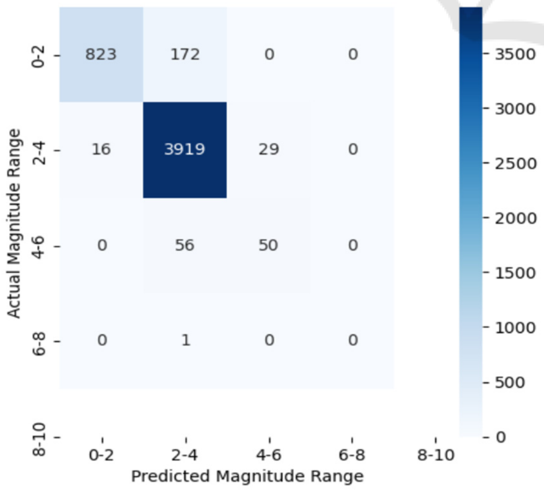

Figure 5. Confusion Matrix for Stacking Model

5 CONCLUSION AND FUTURE WORK

Thus, the proposed work on Earthquake prediction has utilized statistical and ML techniques to predict earthquake magnitudes accurately using a dataset from the Japan region. The proposed model, which combines Random Forest, Extra Trees, CatBoost in a stacking ensemble, and Linear Regression, demonstrated better results. Specifically, the model achieved an MSE of 0.0647, RMSE of 0.2544, MAE of 0.1766, R-squared value of 0.8321, and MAPE of 3.82%, confirming its ability to effectively model complex seismic patterns. When compared to individual models like XGBoost, Gradient Boosting and CatBoost, the stacking model leveraged the strengths of multiple algorithms to improve accuracy and prediction reliability. The stacking ensemble further enhanced generalization and reduced the risk of misclassification, which is common with standalone models. This work underscores the importance of combining various models for seismic analysis and hazard management. The proposed model provides a robust foundation for earthquake magnitude estimation, supporting the development of early warning systems and improving preparedness. The future work will focus on expanding the dataset to include additional seismic features, incorporating IoT for real-time predictions and applying this methodology to other seismic regions. These advancements will contribute to strengthening AI's role in enhancing global disaster resilience.

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