Application Of AI Learning Models In Seismology

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***Abstract*—Natural disasters have devastating effects on human lives and infrastructure. An earthquake is one of the most common natural disasters that have both physically and symbolically rocked people's lives. One of the most challenging problems involves estimating the magnitude and depth of earthquakes. In the fields of seismology and catastrophe science, accurately predicting these factors is still a significant difficulty. Predictions made using current models may be less accurate since they either don't properly account for the intricate dynamics of seismic occurrences or depend too heavily on scant data. To bridge this gap, we propose developing a prediction model that makes use of several machine learning methods, including binary trees, recurrent neural networks, artificial neural networks, and support vector machines. We compare the models in this way to determine which one works better for the given issue statement. Creating a prediction model capable of reliably predicting earthquake depth and size is the main objective of the project. An efficient resource allocation and timely implementation of preventive measures would be made possible by the insights that such a model would offer to catastrophe planning and response teams.**

***Index Terms*—Earthquake prediction, Metaheuristic Optimization, Extreme Gradient Boosting, Random Forest, Recurrent Neural Networks, LSTM, GRU, K-Nearest Neighbors**

I. Introduction

The Earth, an intricate tapestry of geological forces, continually undergoes seismic events that shape landscapes and impact civilizations. These events, known as earthquakes, are both awe-inspiring and potentially devastating. They are unavoidable and cannot entirely be predicted [4].To reduce the effects of such occurrences, numerous national, international, and transnational organizations implement diverse strategies for detecting and preventing disasters. However, constraints like time and resource availability pose challenges for organization managers in effectively allocating these resources [15]. Recognizing the need for advanced understanding and prediction, our project, "Application Of AI Learning Models In Seismology" embarks on a journey into Earth's seismic secrets. Our focal point is an extensive dataset spanning from 1990 to 2023, encompassing a staggering three million entries, each representing a unique seismic occurrence worldwide.

In the realm of seismic exploration, many approaches have been suggested to predict earthquakes, ranging from mathematical analysis to artificial intelligence and machine learning algorithms [7]. By employing algorithms like SVR, RNN, Random Forest, KNN, and XGBoost, we aim to develop a model that can predict not only the occurrence but also the magnitude and depth of earthquakes. The "All the Earthquakes Dataset" obtained from Kaggle, serves as the bedrock of our investigation. With attributes such as date, time, geographical coordinates, magnitude, depth, and affected regions, this dataset offers a comprehensive view of seismic events, empowering our models with historical insights.

Earthquake data, when harnessed effectively, becomes a crucial resource for scientific research and public safety. Through the lens of our dataset, we seek to unravel spatial and temporal patterns, identify high-risk zones, and contribute to the development of accurate predictive models. As we unravel Earth's seismic secrets, this project aims to foster a deeper understanding of seismic activity, ultimately mitigating risks and shaping a safer future for communities worldwide. We're on a mission to predict the unpredictable and make communities earthquake-ready!

II. Literature Review

Using geomagnetic anomalies, Khairul Adib Yusof et al. [1] investigated earthquake prediction models. They employed automated machine learning (AutoML) techniques to compile more than 50 years of global geomagnetic field data from 131 sites. They used a neural network (NN) to obtain an 83.29% accuracy by using the asynchronous successive halving algorithm (ASHA) for model optimization and wavelet scattering transform(WST) for feature extraction.

Debabrata Swain et al. [2] addressed the challenging task of earthquake prediction by developing an intelligent earthquake prediction model using various machine-learning algorithms. Leveraging seismological data from the US Geological Survey (USGS), the model achieves a prediction accuracy of 92.7%.

The study by Zhang Heng et al. [3] proposed a novel approach to earthquake prediction, addressing key challenges such as imbalanced seismic data. By employing a model decoupling methodology that separately trains a backbone network and a classification network, the research effectively mitigated the influence of class imbalance in seismic data.The fusion of these features enabled accurate representation, leading to remarkable performance metrics such as an accuracy rate of 95.8%, a recall rate of 95.8%, and an F1-Score of 0.95.

Raghavendra Reddy et al. [4] proposed a neural network approach for earthquake prediction, emphasizing the need for accurate forecasting to reduce damages. It outperformed traditional methods with 89% accuracy, MAE of 0.2213, and RMSE of 0.4165. Previous studies, like Random Forest and LSTM networks, are discussed.

Rhitik Patil et al. [5] utilized a combination of Artificial Neural Networks (ANN) and Random Forest Regressor to predict earthquake magnitude and depth with a remarkable accuracy of 95%. Their study, based on historical data spanning from 1965 to 2016, highlights the efficacy of integrating ANN with Random Forest Regressor models.

Mohamed S. Abdazaher et al. [6] addressed the critical challenge of discriminating earthquake intensities for effective Earthquake Early Warning Systems (EEWS). Their proposed scheme employed both linear and nonlinear machine learning models. Through comprehensive testing, the XGB model, focusing on features two seconds after the Pwave onset, achieved the most accurate classification of six earthquake intensities. With a classification accuracy of 98.59% for on-site intensity recordings from multiple seismic stations, the XGB model emerged as the best-performing model.

Sadhukhan, B. et al. [7] focused on predicting earthquake magnitudes using deep learning techniques. They mainly proposed a method using eight mathematically calculated seismic indicators and three deep learning models: Long Short-Term Memory (LSTM), Bi-directional Long Short-Term Memory (Bi-LSTM), and transformer models.

Berhich, A. et al. [8] proposes an attention-based LSTM model to predict earthquakes, focusing on large earthquakes. The model leverages clustering based on location and an attention mechanism to improve accuracy. The model is trained on a dataset from Japan and evaluated using multiple metrics (MSE, RMSE, MAE, R-squared, Accuracy). The results show significant improvement over previous methods, especially for magnitude prediction.

Novick, D. et al. [9] investigated the possibility of using machine learning to predict earthquakes. The earthquake data from California, Japan, and Israel was analyzed. Various machine learning models were trained on features extracted from the earthquake data, and their effectiveness in predicting earthquakes was evaluated. The Logistic Regression model achieved the best AUC scores (up to 0.825) for predictions within their respective regions. Models trained on data from one region could be effective in predicting earthquakes in other regions (up to 0.749 AUC score). T Overall, the study suggested that machine learning had the potential to be a valuable tool for earthquake prediction. However, further research was needed to improve the accuracy and reliability of these models.

B. Arunadevi et al. [10] demonstrated the feasibility of employing data mining techniques such as decision trees and geographic information systems to enhance the intelligence of earthquake prediction applications. Overall, the study underscores the importance of automatic intelligencemonitored warning and mitigation systems in addressing the increasing risks posed by earthquakes in populated areas.

Stefan Bloemheuvel et al. [11] investigated a new approach for predicting ground motion during earthquakes using sensor data. The goal is to predict the intensity of ground shaking (PGA, PGV, etc.) at multiple seismic stations based on historical waveform data from those stations. Seismic stations form a sensor network, where each station represents a node in a graph. This method combines CNNs and GNNs. CNNs extract features from the time series data at each station. GNNs then process this data while considering the spatial relationships between stations in the network. This allows TISER-GCN to exploit both the temporal patterns in the waveforms and the geographical context of the sensors. Finally, TISER-GCN is tested on two real-world seismic datasets and compared it to various baseline models, including CNNs and other GNN-based approaches. TISER-GCN outperforms all the baselines on both datasets, demonstrating its effectiveness.

Rachna Jain et al. [12] focused on earthquake magnitude prediction using machine and deep learning models based on position and depth parameters. Utilizing USGS data, it employs Random Forest Regression, Support Vector Regression, and MLP Regression algorithms. Results show MLP Regression outperforms others, achieving the lowest RMSE. The proposed model involves dataset division by radii, model training, and validation. Key findings reveal earthquake magnitude dependence on position and depth. Overall, the study demonstrates the efficacy of deep learning in earthquake prediction, particularly with MLP Regression.

In their research, Wanjiang Han et al. [13] created an earthquake catastrophe prediction model based on the traffic system by utilizing data mining and machine learning approaches. The study contributed to our understanding of the interactions between the earthquake and the traffic system by taking into account variables including earthquake magnitude, intensity, and focal depth in addition to features of the metropolitan traffic system. The authors created reliable prediction models by collecting a large amount of data and training it with techniques such as KNN, SVM, logistic regression, naive Bayes, and decision trees.

Amirul Hoque1 et al. [14] investigated the feasibility of using machine learning techniques for earthquake magnitude prediction. The study proposes an artificial neural network model to predict earthquake magnitudes in four regions: Japan, Turkey, Greece, and the Indian Subcontinent. Data from past earthquakes is used to train the model, focusing on features like time, latitude, longitude, and depth. The model is designed to predict earthquakes with a specific minimum magnitude for each region, 15 days beforehand. Results show the model achieves moderate accuracy, ranging from 78% to 87% depending on the region.

Anmol et al. [15] discovered that the Random Forest Classifier (RFC) method showed superior predictive accuracy in diagnosing earthquake damage compared to Logistic Regression (LR), Naive Bayes Classifier (NBC), and K-Nearest Neighbors (KNN). They determined this based on the RFC's highest F1 score, suggesting its effectiveness in assessing structural damage caused by earthquakes.

In the investigation conducted by Roxane et al. [16], various machine learning algorithms were scrutinized for their efficacy in earthquake prediction. Leveraging a dataset sourced from the earthquake data center in Northern California, the study trained and tested models using algorithms such as Random Forest, Naive Bayes, Linear Regression, Multi-Layer Perceptron, K Nearest Neighbours, AdaBoost, Support Vector Machine, and CART. Notably, the Random Forest algorithm exhibited the highest accuracy among the models, achieving a remarkable accuracy rate of 76.97%.

Asim et al. [17] examined earthquake prediction using four boosting algorithms such as PRNN, RNN, RF, and LP, and eight seismicity parameters were used as classifier inputs. Each classifier yielded slightly different results, with the Linear Programming Boost ensemble classifier showing superior sensitivity and the Pattern Recognition Neural Network minimizing false alarms. LP Boost achieved the highest accuracy of 65for unseen data, followed by RNN at 64%. PRNN exhibited the fewest false alarms.

III. PRELIMINARIES

This section thoroughly describes the study's dataset, including information on its features and structure. We also describe in detail the performance evaluation metrics used to evaluate and compare the accuracy of various models in predicting the occurrence of earthquakes.

A. *Dataset Description*

The dataset used in our study has been downloaded from Kaggle titled **"All the Earthquakes Dataset: from 1990-2023 "**. The dataset consists of 34,45,751 observations with 12 features described in table I. [1].

The earthquake dataset is a comprehensive compilation spanning 1990 to 2023, comprising around three million entries, each representing a specific earthquake event. Entries include attributes like event date, time, geographical coordinates, magnitude, epicenter depth, measurement type, affected region, and other relevant details, offering a detailed overview of global seismic activity.

The dataset holds immense significance across various domains. For earthquake analysis and prediction, it serves as a valuable resource, enabling scientists to study spatial and temporal distribution patterns, identify high-risk zones, and develop precise predictive models. In terms of safety and prevention, understanding earthquake factors aids authorities in implementing preventive measures globally, enhancing the design of earthquake-resistant structures. Making earthquake data public fosters awareness, enabling preparedness and contributing to scientific research, public safety, and community awareness, thereby mitigating seismic risks.

B. *Performance Evalution Parameters*

*1) **R2 Score**:* The formula for calculating the R^2 score, also known as the coefficient of determination, is:

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

Where: - y_i is the observed value of the target variable. - $\hat{y}_i$ is the predicted value of the target variable. - $\bar{y}$ is the mean of the observed values of the target variable. - n is the number of samples.

In simpler terms, R^2 is calculated as the proportion of the variance in the dependent variable that is predictable from the independent variables. It measures how well the model fits the data, with higher values indicating better fit.

*2) **Mean Absolute Error**:* The Mean Absolute Error calculates the average difference between the calculated values and actual values. It is given by:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2}$$

where **n** represents the number of samples, y_i represents the actual value for the sample, and $\hat{y}_i$ represents the actual value for predicted the sample.

[1]https://www.kaggle.com/datasets/alessandrolobello/the-ultimate-earthquake-dataset-from-1990-2023/data

TABLE I
DATASET DESCRIPTION

Feature	Type	Description
time	int64	time in milliseconds.
place	object	geographical location.
status	object	Represents the current state or condition of the event, which could be reviewed or automatic.
tsunami	int64	Relates to a series of large ocean waves typically caused by an underwater disturbance, often associated with.
significance	int64	Denotes the importance or impact level of the event, which could be used to assess the potential consequences.
datatype	object	Specifies the type of data being referenced.
magnitudo	float64	Refers to the measurement of the size or intensity of an earthquake, typically measured on the Richter.
state	object	Represents the administrative division or state where the event occurred, often applicable to specific countries.
longitude	float64	coordinate float.
latitude	float64	coordinate float.
depth	float64	depth of the effect caused.
date	object	date when occurred.

*3) **Mean Squared Error**:* The Mean Squared Error calculates the average of the square of the difference between the calculated values and actual values. It is given by:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (3)$$

where **n** represents the number of samples, **y** represents the actual value for the sample, and **yhat** represents the actual value for predicted the sample.

*4) **Root Mean Squared Error**:* The Root Mean Squared Error calculates the square root of the average of the square of the difference between the calculated values and actual values. It is given by:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (4)$$

where **n** represents the number of samples, y_i represents the actual value for the sample, and $\hat{y}_i$ represents the actual value for predicted the sample.

IV. PROPOSED METHODOLOGY

This section delineates the procedural sequence adopted for earthquake prediction. The proposed methodology encompasses the following stages: 1. Data preprocessing 2. Data Splitting 3. Metaheuristic Optimization and 4. Models Implementation. These steps in the proposed methodology are illustrated in Fig. 1.

*A. **Data Preprocessing***

The preprocessing stage involves several data manipulation tasks to prepare the dataset for modeling. First, the dataset is cleaned up to remove superfluous columns like ”place,” ”status,” ”datatype,” ”state,” and ”date” to concentrate on important features. To guarantee data completeness, rows with missing values are also eliminated. Moreover, label encoding techniques are used to encode categorical information. The categorical variable ’tsunami’, for example, is encoded with a label encoder to translate its categorical values into numerical representations.

*B. **Data Splitting***

At this stage, the dataset is partitioned into two subsets: the training set and the testing set. In our instance, the value is set to 0.2, indicating that 20% of the data will be used for testing purposes, while the remaining 80% will be utilized for training. The process of splitting the data is crucial for evaluating the trained model's ability to perform on new, unknown data. This step allows us to examine the model's generalization and detect any potential problems, such as overfitting.

*C. **Metaheuristic Optimization***

A Metaheuristic Optimization called Particle Swarm Optimization (PSO) is used in our study to select the most optimal subset of features for training the models. Particle Swarm Optimization (PSO) is specifically influenced by the collective behavior of birds flocking or fish schooling. It has been proven to be highly effective in various optimization problems, such as feature selection.

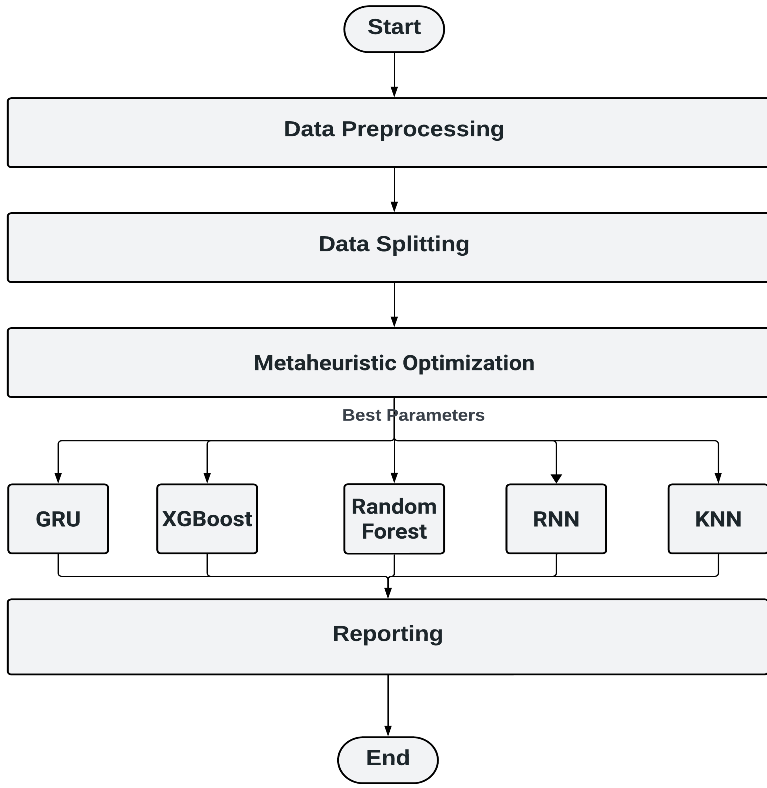

Fig. 1. Proposed Workflow

Here is a detailed description of the procedure and the underlying reasoning for employing metaheuristic optimization:

- The fitness function was defined to assess the effectiveness of potential solutions. It involved training the model with selected features and computing Mean Squared Error (MSE) on the test data, with the objective of minimizing MSE. Negative MSE was returned to maximize fitness.
- The optimizer was initialized by setting the PSO hyperparameters, including cognitive and social components, as well as the inertia weight. These parameters were balanced to facilitate both exploration and exploitation.
- PSO optimization was conducted by updating particle positions based on fitness values and the best positions discovered. This iterative process continued for a predetermined number of iterations.
- Feature selection was performed by analyzing particle locations to identify an optimal feature set for subsequent examination.

D. Models Implemented

Following the selection of features through metaheuristic optimization using PSO, several machine learning models were implemented, including Extreme Gradient Boosting (XGBoost), Random Forest, LSTM-based RNN, GRU-based RNN, and finally K-Nearest Neighbors (KNN). For the LSTM and GRU models, the training process was conducted over 30 epochs with a batch size of 16. Additionally, KNN was employed with cross-validation using grid search to fine-tune the model parameters.

*1) **Extreme Gradient Boosting**:* XGBoost emerges as a robust open-source toolkit designed to address a spectrum of machine learning challenges, encompassing regression, classification, and ranking tasks. Its standout features include Efficiency, Precision, and Versatility. The amalgamation of speed, accuracy, and adaptability renders XGBoost a favored tool among data scientists in fields spanning finance, e-commerce, natural language processing, computer vision, and bioinformatics.

*2) **Random Forest**:* It operates by training individual trees on randomized subsets of data and features, subsequently combining the predictions to produce an outcome. This characteristic renders them resilient and adaptable for various classification and regression assignments. During the construction of each decision tree, it takes into account a criterion referred to as the Gini Index, which quantifies the information gain, as demonstrated in the equation 5.

$$Gini = 1 - \sum_{\mathrm{i}=1}^{\mathrm{c}} (\mathrm{p_i})^2 \tag{5}$$

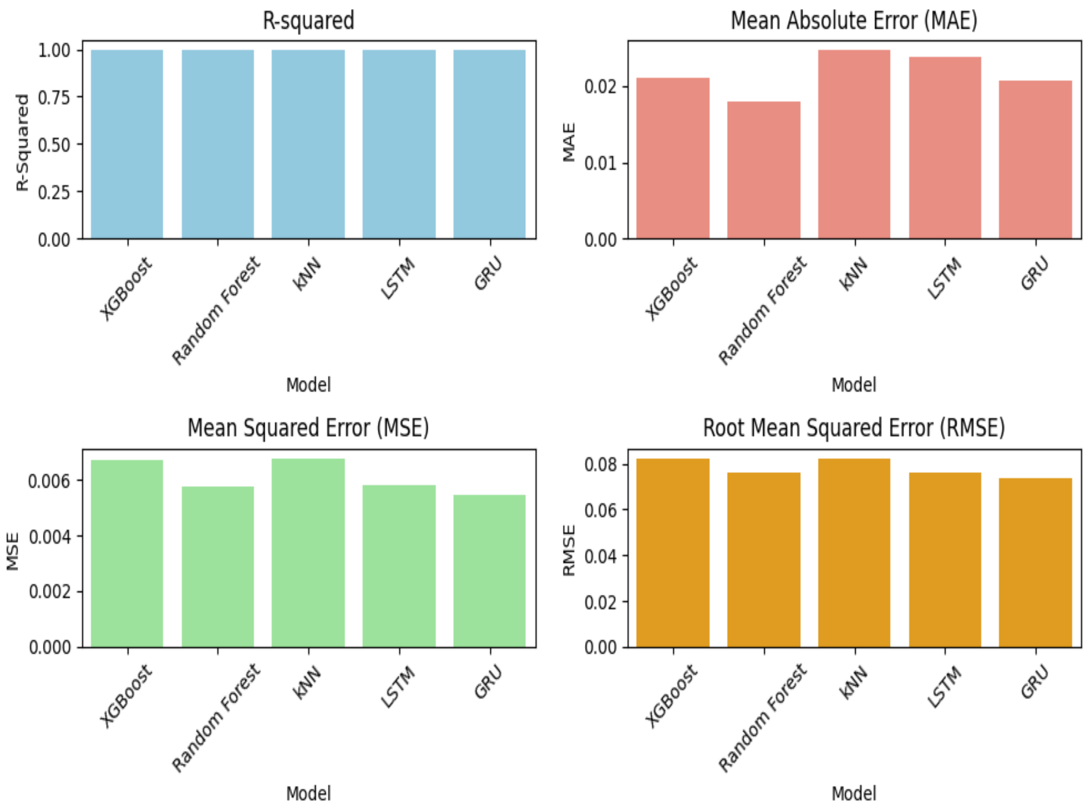

Fig. 2. Results

*3) **Recurrent Neural Networks**:* RNNs excel with sequential data such as language, speech, or time series. Unlike conventional neural networks, RNNs possess memory, enabling them to learn from previous inputs and shape their processing of current ones. This capability is advantageous for tasks like machine translation or forecasting, where grasping context is crucial. Nonetheless, RNNs may encounter difficulties with lengthy sequences.

- **LSTM-based RNN** - LSTMs or Long Short-Term Memory networks, represent a specialized variant of recurrent neural networks crafted to address the challenge of vanishing gradients encountered in lengthy sequences. In contrast to employing a singular equation, LSTMs leverage interconnected gate mechanisms—namely forget input, and output gates—to regulate the flow of information within a cell state, commonly referred to as memory. These gates utilize activation functions alongside element-wise operations to perform computations effectively.
- **GRU-based RNN** - The GRU (Gated Recurrent Unit) represents a simplified form of recurrent neural network also tailored to mitigate the issue of vanishing gradients. Diverging from LSTMs, which integrate three gates, GRUs incorporate two essential components:
  - Reset gate: Dictates the extent to which preceding information (hidden state) is disregarded.
  - Update gate: Regulates the balance of information transfer between the past (hidden state) and the current input to generate a fresh hidden state.

  These gating mechanisms rely on learned parameters including weight matrices, bias terms, and activation functions, which are optimized during the training process. Despite lacking a singular formula, GRUs adeptly capture prolonged dependencies within sequences.

*4) **K-Nearest Neighbors**:* KNN (K-Nearest Neighbors) stands as a widely used machine learning algorithm for both classification and regression tasks. Its operation involves identifying the nearest data points (neighbors) to a new data point and leveraging them to forecast the class or value of the new data point [16]. KNN is known for its simplicity and effectiveness across numerous problem domains, yet it may pose computational challenges with sizable datasets.

TABLE II
MODEL PERFORMANCE METRICS

Model	**R-Squared**	**MAE**	**MSE**	**RMSE**
XGBoost	0.9949	0.0211	0.0067	0.0819
Random Forest	0.9956	0.0179	0.0058	0.0760
kNN	0.9949	0.0247	0.0068	0.0824
LSTM	0.9956	0.0238	0.0058	0.0761
GRU	0.9959	0.0206	0.0054	0.0737

Results and Conclusion

Machine Learning Algorithms combined with Particle Swarm Optimization was able to effectively predict the depth and magnitude of earthquakes. The GRU based RNN model showed the performance among them demonstrating predictive accuracy and generalization ability. PSO played a role in selecting features improving model performance by choosing the relevant ones for training. In summary the study indicates that deep learning models, those based on neural networks like LSTM and GRU surpassed traditional machine learning algorithms such as XGBoost and Random Forest in earthquake prediction tasks. These integrated with real time data feeds will be powerful tools for disaster management.

Future Work

There are a few areas in which we can improve and continue our work. Including data sources, like satellite images, geological surveys, and social media data can improve the precision and dependability of earthquake prediction models. Delving into in-depth studies to pinpoint geological traits and environmental elements that impact seismic events can aid in creating customized prediction models for various areas. Connecting our models, with real-time data feeds enables them to assess tremors as they occur and send out alerts. However, it's important to consider how we can identify alarms and manage them effectively.

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