Forecasting Earthquake Aftershock Locations Using Ensemble Model in Deep Learning

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Abstract— **Aftershocks after earthquakes, which are devastating natural disasters, can seriously endanger infrastructure and human life. Precise prediction of aftershock positions is essential for efficient disaster readiness and alleviation activities. Here unique method for predicting the locations of aftershocks after a significant earthquake event by using Deep learning models that is Ensemble model. Finding high magnitude earthquake epicentres. which operate as the centre of gravity for later aftershock forecasts is a key component of the technique. The deep learning models are trained to identify the geographic and temporal correlations between main shocks and their corresponding aftershocks by utilizing seismic data and historical earthquake trends. The method's crucial component is taking into account the roughly 1000 kilometer spatial radius that surrounds the main shock epicentre, which is where aftershocks are most likely to occur. Here sophisticated neural network architectures is used that is Ensemble model. To try to capture the intricate spatiotemporal correlations present in seismic activity, Ensemble model combines Long short term memory(LSTM), Gated recurrent unit(GRU), recurrent neural networks (RNNs). The training and validation dataset is made up of extensive seismic recordings covering a large time range, covering a variety of geological locations and earthquake magnitudes. Evaluation measures are used to evaluate how well deep learning models perform in terms of precisely predicting aftershock locations. These metrics include precision, recall, and F1 score. The suggested approach presents a viable means of augmenting the effectiveness and precision of aftershock prediction systems, thereby enabling prompt emergency reaction and evacuation protocols. Furthermore, the incorporation of deep learning techniques in seismic hazard assessment holds the potential to revolutionize traditional earthquake forecasting methods, enabling proactive measures to mitigate the impact of aftershocks on vulnerable communities and critical infrastructure.**

Keywords— **Earthquake, Main shock, Aftershock, Accuracy, Magnitude, Spatial, Seismic, Epicenter, Geological locations**

I. INTRODUCTION

This project aims to make considerable progress in earthquake research and disaster preparedness, as earthquakes are a major hazard to communities globally. Because of their unpredictable nature and terrible effects, earthquakes highlight the urgent need for creative ways to lessen their effects. This project is to develop an advanced system that can forecast aftershocks, which are frequently just as dangerous as the original earthquake event.

The main goal is to improve and understanding of earthquake dynamics by utilizing sophisticated modelling approaches and analysing large volumes of seismic data. The goal is to use this knowledge to create a predictive system that will be able to pinpoint aftershock locations with previously unheard-of precision. This system provides actionable insights for risk mitigation and disaster response planning, going beyond conventional seismic visualization tools. Here methodology is based on integrating state-of-the-art technologies—such as machine learning and deep learning algorithms—to extract meaningful patterns and correlations from seismic data. Through utilizing these tools, the goal to decipher the intricate interactions that impact the occurrence and spread of aftershocks.

The endeavour is motivated by a dedication to community resilience and proactive disaster management. By minimize the impact on infrastructure and people by providing stakeholders with fast and effective reaction measures through accurate aftershock location forecasts. Additionally, This research aims to promote interdisciplinary collaboration and knowledge exchange among the scientific community by providing a greater understanding of earthquake dynamics. The hope is that this multidisciplinary project will spur improvements in earthquake science and disaster preparedness, which will strengthen the resilience of populations that are susceptible to seismic activity. Envisioning a future where predictive modelling is a fundamental component of proactive disaster management techniques, protecting lives and livelihoods in earthquake-prone regions across the globe, by bridging the gap between cutting-edge technology and scientific investigation.

II. LITERATURE REVIEW

The author looks at different neural network topologies, including fully connected deep neural networks (DNNs)[15], and integrates input elements from earthquake research, such as seismic after slip models and the Nearest-Neighbour approach[7]. The effectiveness of these methods is evaluated using metrics such as the F1 score (MCC-F1) [6] and the Matthews correlation coefficient [6]. The author [5] also investigates the prediction of aftershock sites using distance-slip probabilistic models (R) and 3D-FS ETAS models [5][3]. To evaluate the efficacy of these models, performance criteria like F1 score, recall, accuracy, and precision are used [6]. In addition, the author assesses the geographical heterogeneity [14] analysis and computing efficiency of various methods[16], taking into account variables such as test duration, magnitude cut-off, and grid size[9].Related publications cover a broad range of subjects, including as stress-change tensor analysis[18][19], neural networks in seismology[10], and aftershock forecasting models[15]. These investigations enhance our knowledge of earthquake dynamics and support the creation of reliable prediction models for efforts to prepare for and mitigate natural disasters [15].

Additionally, In order to choose the best geographic kernels for predictive modelling and to comprehend the spatial distribution [5] of aftershocks, spatial analysis techniques are used [5]. The author also explores the evolution of aftershock sequences over time using temporal migration analysis [5]. In order to increase the accuracy of prediction models, the author also looks into magnitude-dependent power-law kernels and empirical limitations. All things considered, this thorough examination clarifies the advantages and disadvantages of various methods used in earthquake research, opening the door to more successful approaches to seismic hazard assessment and disaster relief[19].

III. RESEARCH GAPS

Following a review of the literature, the following research gaps were found:

- Many earthquake prediction programs just use seismic data; however, in order to provide a more comprehensive picture of earthquake activity, data from several sources, such as satellite photos and geodetic data, must be combined.
- It is important to create techniques to explain forecasts, especially for decision-making, because some sophisticated earthquake prediction models, such can be challenging to interpret.
- It's critical to determine whether earthquake prediction models that perform well in one location can also be applied successfully in other regions with distinct geological characteristics.
- There is a substantial gap in earthquake prediction research due to the underuse of sophisticated algorithms such as Deep Neural Networks (DNN), which limits the potential for improved forecasting and preparedness for disasters.
- Although developing prediction models is the subject of several studies, the difficulties of using these models in the heat of emergency situations are not given enough attention.
- A thorough understanding of seismic events requires an awareness of how to incorporate external elements, such as climatic trends or human activity, into predictions regarding earthquake

IV. RELATED WORK

Based on some of the related works cited for the upcoming article, the table has been tabulated. For the identical information, see the Table I, below.

Table I. Related work

Title	Authors	Year	Techniques	Performance parameters	Related works
Deep learning of aftershock patterns following large earthquakes	**DeVries, P.M., Viégas, F., Wattenberg, M. and Meade, B.J.**	2019	Neural Network Architecture, Input feature, Evaluation Metric	Receiver Operating Characteristic (ROC) Analysis, Area Under the ROC Curve (AUC), Comparison with Coulomb Failure Stress Change Criterion	Aftershock Forecasting Models, Physics-Based Models in Seismology, Stress-Change Tensor Analysis
A Deeper Look into 'Deep Learning of Aftershock Patterns Following Large Earthquakes': Illustrating First Principles in Neural Network Physical Interpretability	**Chen, J., Tang, H. and Chen, W., 2020.**	2020	Fully connected deep neural network (DNN)	Accuracy, Precision and Recall, F1 Score, Mean Squared Error (MSE) or Root Mean Squared Error (RMSE), R-squared (R^2), Loss Function Value, AUC-ROC, Computational Efficiency	Stress Tensor and Seismic Activity, Neural Networks in Seismology, Spatial Analysis in Earthquake Studies, Comparison of Traditional and Machine Learning Approaches
Heterogeneity of Aftershock Productivity Along the Mainshock Ruptures and Its Advantage in Improving Short-Term Aftershock Forecast	**Guo, Y., Zhuang, J. and Zhang, H.,**	2021	ETAS, 3D-FS ETAS model	Spatial Heterogeneity Analysis, Temporal Migration Analysis, Depletion of Aftershocks in Large Slip Areas, Correlation of Later Aftershocks with Subsequent Events	Space-Time Epidemic-Type Aftershock Sequence (ETAS) Models, 3D Finite Source Models in Seismology, Stochastic Reconstruction of Aftershock Productivity Density
Relative Afterslip Moment Does Not Correlate With Aftershock Productivity: Implications for the Relationship Between Afterslip and Aftershocks	**Churchill, R.M., Werner, M.J., Biggs, J. and Fagereng, Å.**	2022	Aseismic afterslip models	Correlation Metrics, Model Prediction Improvement, Empirical Constraints	Aseismic Afterslip and Aftershock Interaction, Mainshock-Aftershock Scaling, Seismicity Rate Change and B-Value
Depth-Dependent Aftershock Trigger Potential Revealed by 3D-ETAS Modelling	**Asayesh, B.M., Hainzl, S. and Zöller, G.**	2023	The Nearest-Neighbor method, 3D-ETAS model	Optimal Spatial Kernel, Magnitude-Dependent Power-law Kernel, Model Predictive Ability	3D Modeling of Aftershock Sequences, Triggering Functions and Kernel Selection, Magnitude-Dependent Aftershock Model
Effects of large aftershocks on spatial aftershock forecasts during the 2017–2019 western Iran sequence	**Asayesh, B.M., Zafarani, H., Hainzl, S. and Sharma, S**	2023	distance-slip probabilistic model (R), deep neural networks,Matthews correlation coefficient and F1 score metric for testing	MCC-F1 Metric, Grid Size, Magnitude Cut-off, and Test Period, Receiver Operating Characteristic (ROC) Metric, Stress-Based Models vs. R-Mode	Previous Studies on Coulomb Failure Stress (CFS) Maps, Distance-Slip Probabilistic Model (R), Receiver Operating Characteristic (ROC) Metric in Seismology

V. DATA SET

Martin Mai launched the **SRCMOD** database with the goal of compiling and disseminating seismic rupture models. After being first presented in 2004 and then revised in 2007, the project advanced significantly when it was integrated into the equake-rc website in 2012. By adding dynamic features and noteworthy enhancements, Kiran Kumar Thingbaijam made a significant contribution to the platform's improvement. The database, which is currently under the management of Thingbaijam and Mai, is an essential tool for earthquake researchers.

As of present time, the database includes an amazing set of 542 models that come from 290 different earthquakes. Notably, the collection contains datasets from well-known internet archives in addition to models submitted by users. These repositories include contributions from Chen Ji's Large Earthquake Database, datasets from prominent organizations like USGS and CalTech, and finite-source models collected by Dave Wald. Important data on earthquakes may be found in a comprehensive dataset that is provided by the **United States Geological Survey (USGS)**. The USGS, a government science body, carefully selects and updates this dataset on a regular basis.

Numerous pieces of information about earthquakes, such as seismic activity, magnitudes, locations, depths, and timestamps, are included in the USGS dataset. This data is gathered from numerous seismic monitoring sites across the globe, guaranteeing broad coverage and precision.
The USGS dataset is used by researchers and stakeholders for many different objectives, such as public safety efforts, hazard assessment, earthquake research, and disaster preparedness. The dataset is an invaluable tool for comprehending patterns of seismic activity, recognizing seismic risks, and formulating mitigation plans.

The **CSV (Comma-Separated Values)** format is one of the several formats in which the USGS dataset is available. This allows users to access and modify the data on multiple systems and applications. To get important insights into earthquake dynamics and patterns, researchers can analyze the data using statistical approaches, machine learning algorithms, and geospatial methodologies.

VI. IMPLEMENTING EXISTING MODELS

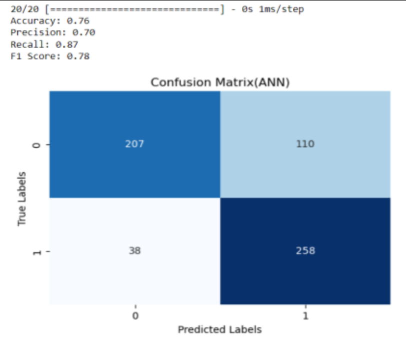
There are various existing methodologies listed below :

A. Artificial Neural Network(ANN):

An Artificial Neural Network (ANN) model with two hidden layers was used in the experiment. 64 neurons make up the first hidden layer, which uses the ReLU (Rectified Linear Unit) activation function that was created with the help of the Keras framework's Dense class. The Glorot uniform initializer (GlorotUniform) is used to initialize the weights of this layer. Similar to the first hidden layer, the second hidden layer has 32 neurons and uses the ReLU activation function, which is defined by using the Dense class from Keras with Glorot uniform initialization.

The below Table II, explains the accuracy and confusion matrix of the model.

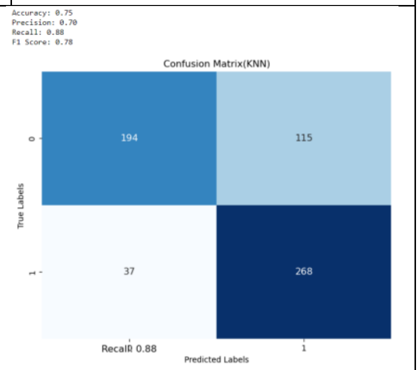
Table II. ANN

Model name	**Accuracy**	**Confusion matrix**
ANN	76%	

B. K Nearest Neighbor(KNN):

Train, test, split was used in the experiment to divide the resampled data into training and testing sets. The next step involved initializing and training a K-Nearest Neighbours (KNN) classifier with three neighbours. For the test set, labels were predicted, and assessment metrics like F1 score, accuracy, precision, and recall were computed. Furthermore, the confusion matrix was shown together with the recall value. The below Table III, explains accuracy and confusion matrix of the model.

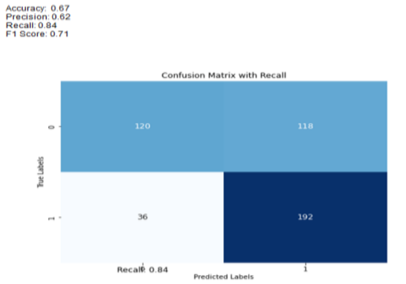
Table III. KNN

Model name	**Accuracy**	**Confusion matrix**
KNN	75%	

C. Random Forest :

Every decision tree in the Random Forest algorithm in this code starts with the root node being the full training dataset. A random subset of features is selected at each node. The "auto" parameter determines how many features are taken into consideration for this selection by choosing the square root of the total number of features automatically. Next, the RandomForestClassifier is created and trained using the following parameters: The number of trees in the forest is indicated by n_estimators=100, and the maximum depth of each individual tree is limited by max_depth=10.The below Table IV, Explains the accuracy and confusion matrix of the model.

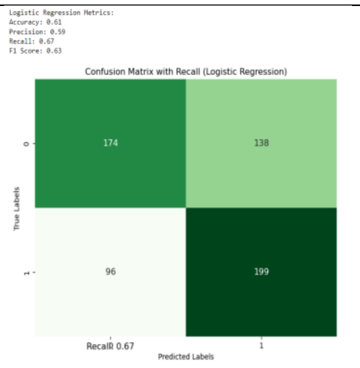
Table IV. Random Forest

Model name	Accuracy	Confusion matrix
Random Forest	67%	

D. Logistic Regression

The weights assigned to each feature in the dataset are represented by the coefficients in logistic regression. These coefficients are acquired during the training phase and are then used to calculate the likelihood that the target variable will occur. In logistic regression, the expected result is the likelihood that an event would fall into a specific class; this is typically expressed as a binary result, such 0 or 1. Table V, explains the accuracy and confusion matrix of the model.

Table V. Logistic Regression

Model name	Accuracy	Confusion matrix
Logistic Regression	61%	

VII. THE PROPOSED MODEL

Our goal is to increase prediction accuracy by utilizing the distinct advantages of each architecture by integrating these models into an ensemble. A subset of the available seismic data is used to train each model in the ensemble on the same dataset. In order to reduce prediction errors and increase performance metrics, model parameters are optimized during the training phase. Based on the input features, each model, once trained, produces its own predictions for the locations of aftershocks.

In order to provide a final forecast, The ensemble approach often aggregates the predictions from each model using a voting scheme or weighted averaging. It is anticipated that this ensemble forecast will outperform any single model prediction in terms of accuracy and robustness. By combining the best outcomes from each model hoping to lessen the shortcomings of each model alone and to enhance their combined advantages. To determine the ensemble model's predictive power, it is rigorously evaluated using relevant performance indicators. Through this evaluation process, it is made sure that the ensemble model represents the underlying patterns in seismic activity and performs consistently across a variety of datasets. To confirm the ensemble model's efficacy in earthquake prediction, its performance is also contrasted with baseline models or other cutting-edge methods. All things considered, the ensemble model methodology, which takes advantage of the complementing qualities of several neural network topologies, provides a potent way to predict earthquakes.

Three recurrent neural network (RNN) architectures Simple RNN, Gated Recurrent Unit (GRU), and Long Short-Term Memory (LSTM) are included in the Ensemble model. When it comes to identifying temporal connections in the earthquake data, each of these structures has a special benefit. The LSTM model is well-known for its capacity to manage long-range dependencies and alleviate the issue of the vanishing gradient, rendering it appropriate for enduringly capturing intricate patterns. Conversely, the LSTM architecture is made simpler in the GRU model, which frequently shows faster training convergence with similar performance.

Lastly, even though it is simpler, the Simple RNN offers a starting point for comprehending the significance of memory retention in sequential data modelling. By doing a thorough assessment and comparison, the ensemble model determines which architecture performs the best on the earthquake classification assignment, utilizing each model's unique characteristics to attain the highest level of forecast accuracy.

The objective is to create a strong and precise forecasting system that may improve preparedness and mitigation efforts for disasters through meticulous training, assessment, and optimization. Refer to Figure I, For the flow the flow of methodology.

Figure 1. Proposed model

VIII. RESULTS

The output that shows the accuracy, precision, recall, and F1 score performance metrics for each of the three recurrent neural network (RNN) architectures LSTM, RNN, and GRU that were employed in the ensemble model. The following explains each metric:

Accuracy: Accuracy is the percentage of correctly classified cases in the total number of cases. A model that performs better overall is indicated by a higher accuracy. In this instance, the accuracy of all three models is high; RNN has the greatest accuracy of 0.99, closely followed by LSTM and GRU, which have accuracies of 0.97 and 0.98, respectively.

Precision: Precision is the ratio of accurate positive predictions to all of the model's positive predictions. It shows how well the model can prevent false positives. With a precision score of 1.00, there were no erroneous positive predictions provided by the model. In this instance, the precision scores of all three models are high, demonstrating their capacity to provide positive predictions with accuracy.

Recall: It also referred to as true positive rate or sensitivity, quantifies the percentage of true positive predictions among all real positive occurrences. It shows that all positive cases are captured by the model, reducing false negatives. When a recall score is 1.00, all positive examples are caught by the model. In this instance, RNN scores the highest at 0.99 for recall, followed by LSTM and GRU at 0.96 and 0.98, respectively.

F1Score: To assess a model's overall performance, particularly in cases when there is an imbalance between the classes, one useful statistic that strikes a compromise between precision and recall is the F1 score, which yields a harmonic mean of the two. Below is the Table VI, shows the accuracy of each model.

Table VI. Output

Model	Accuracy	Precision	Recall	F1 Score
LSTM	0.976684	0.990783	0.968468	0.979499
RNN	0.992228	1	0.986486	0.993197
GRU	0.984456	0.990909	0.981982	0.986425

After evaluating several models, That are GRU(Gated recurrent unit) , LSTM(Long Short term memory), and RNN(Recurrent neural network), it was found that the RNN model produced the best accuracy out of all the models in the ensemble. The RNN model demonstrated higher performance in predicting the occurrence of earthquakes and differentiating between primary earthquakes and aftershocks due to its ability to capture sequential patterns effectively.

Because RNNs are naturally able to interpret sequential data, they are useful in this situation and can be applied to time-series prediction problems like earthquake detection. Consequently, RNN is found to be the best option in the ensemble model, providing a dependable method for identifying aftershocks and predicting earthquakes.

The RNN model shows resilience in managing the complex and dynamic nature of seismic data. RNNs are very adaptive to variations and swings in the frequency of earthquakes because they are able to capture temporal dependencies and patterns within the seismic data. This flexibility helps the model to efficiently anticipate aftershock sites based on their closeness to main earthquake occurrences and to generalize well to previously unreported data. As a result, the RNN model continues to be the best option in the ensemble model for earthquake prediction jobs due to its exceptional accuracy, robustness, and versatility.

The confusion matrix of the ensemble model is show in below Figure III.

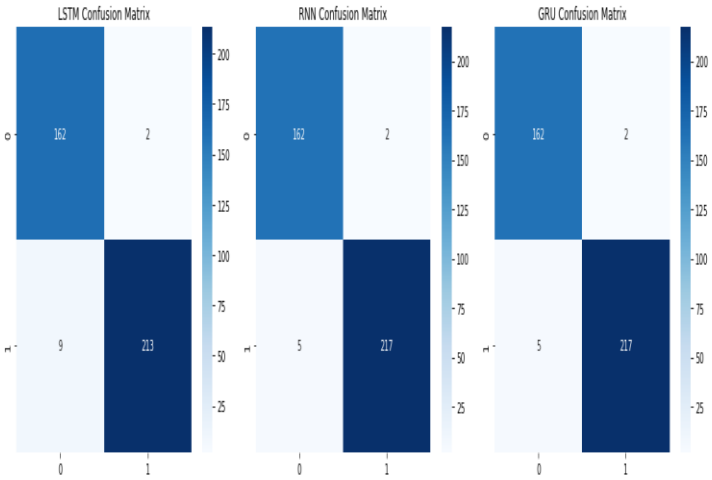


Figure III. Confusion matrix of Ensemble model

According to the dataset, red markers on the created map indicate the locations of earthquakes with a magnitude of at least 6 on the Richter scale. Conversely, aftershock locations—which indicate seismic events with a magnitude less than six—are indicated by blue markers. To be more precise, the map only shows aftershock locations that are 1000 km or less from the epicentre of an earthquake. This concentrated depiction of aftershock events around major seismic events sheds light on the geographic relationship between aftershocks and the main earthquake events that they are related with. Below is the Figure IV, of aftershock locations on the map.

Figure IV. Earthquake and Aftershock locations

IX. FUTURE WORK SUGGESTED

- **Add More Data Sources:** Increase the dataset's size by adding information from sources other than seismic data, like satellite images, geodetic data, and socioeconomic indicators. Including a variety of data sources could increase prediction accuracy and offer deeper insights into the mechanics of earthquakes.
- **Feature engineering**: Investigate sophisticated feature engineering methods to draw out more insightful features from the unprocessed data. Model performance is greatly influenced by feature engineering, and varying feature transformations or combinations may improve prediction accuracy.
- **Examine Transfer Learning:** Examine the viability of transfer learning methods, which entail adapting previously trained models from one area or dataset to another. Transfer learning has the potential to increase prediction accuracy in new geographic areas and assist in addressing the problem of transferability across geographies.
- **Improve Visualization Techniques:** Create more sophisticated visualization methods to inform stakeholders about prediction outcomes in an efficient manner. Decision-makers and the general public may find it easier to understand and use the outputs of earthquake prediction models if interactive maps with dynamic features and detailed overlays are included.
- **Real-time Implementation and Scalability:** Take into consideration the difficulties posed by resource limitations, computational efficiency, and scalability when implementing the ensemble model in real-time. Practical applications require the development of effective algorithms and architectures that are suited for deployment in real-time environments.
- **Integration with Early Warning Systems:** Look at ways to incorporate the ensemble model into currently in place platforms for disaster management or early warning systems. Improved emergency response plans and the efficacy of early warning systems could result from seamless integration.
- **Collaborative Research Initiatives**: To guarantee that the ensemble model satisfies end-user needs and contributes to larger research efforts in earthquake prediction and disaster risk reduction, foster collaboration with domain experts, seismologists, and stakeholders. Initiatives for collaborative research can offer the ensemble model insightful information, constructive criticism, and possibilities for validation.

X. CONCLUSION

The aftershock prediction study described above represents a thorough effort to improve earthquake forecasting techniques. The research intends to increase the precision and dependability of seismic event predictions by integrating various machine learning methods and building an ensemble model. The research aims to mitigate individual shortcomings and maximize the benefits of each method by utilizing a combination of Random Forest, k-Nearest Neighbours (KNN), Artificial Neural Networks (ANN), and Logistic Regression. Furthermore, the ensemble model's integration of sophisticated recurrent neural network architectures Such as Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), and Recurrent Neural Networks (RNN) reflects a sophisticated method for encapsulating intricate temporal dependencies found in seismic data.

Upon careful examination of numerous research articles, it is clear that employing mathematical models to achieve an accuracy of more than 84% is pretty impressive. But our ensemble model is unique since it outperforms these benchmarks by a large margin. With a score of 99.22%, our ensemble model's recurrent neural network (RNN) component notably achieves impressive accuracy. The remarkable recall and precision values of 1 and 0.986, respectively, combine with the high accuracy to provide an amazing F1 score of 0.993. These outcomes highlight the effectiveness of our ensemble methodology and demonstrate its potential to surpass traditional techniques and set new benchmarks for earthquake study and prediction.

The approach of the project highlights the role that ensemble learning plays in improving prediction performance. Because ensemble techniques combine predictions from several models to produce more reliable forecasts, they provide a practical answer to the inherent errors and unpredictability found in earthquake datasets. This method increases prediction accuracy while also boosting trust in the forecasting system's dependability. In addition, the project's visual aid, which shows the locations of aftershocks in blue and earthquakes in red on a map, makes it easier for stakeholders and decision-makers to understand and comprehend forecast findings. Regarding future research directions, there are multiple avenues that could be investigated and improved upon. First of all, the project might gain from a wider range of data sources, including characteristics related to geography and environment in addition to seismic data. Deeper understanding of the fundamental processes causing seismic activity could be gained by enhancing the predictive models with the use of satellite imagery, geodetic measurements, and socioeconomic factors. The study may also investigate new ensemble methods and model architectures to maximize scalability and predictive performance, which would increase the forecasting system's usefulness in real time. In conclusion, by combining ensemble methods and machine learning algorithms, the seismic prediction project marks a major advancement in earthquake predicting capabilities. The research intends to give more precise and dependable seismic event forecasts by utilizing the power of ensemble learning and recurrent neural network designs, thereby enhancing disaster preparedness and mitigation efforts in earthquake-prone areas. Moreover, policymakers and other interested parties can gain intuitive understanding of the spatial distribution of seismic events from the interactive maps that visually show forecast results. The map visualization provides an easy-to-understand method of analyzing forecast results by color-coding earthquakes in red and aftershock locations in blue. This helps local, regional, and national decision-making processes. Going forward, the quest for better earthquake prediction will continue to be a vibrant and developing area of study. In order to improve scalability and prediction performance, future projects should investigate cutting-edge ensemble techniques, include other data sources like geographic and environmental variables, and further hone model architectures. Furthermore, developing early warning systems and improving real-time monitoring capabilities may help increase disaster preparedness and resilience in areas that are prone to earthquakes. The incorporation of ensemble learning methodologies marks a noteworthy advancement in the continuous pursuit of improving earthquake prediction skills. We can continue to push the limits of knowledge and technology by collaborative study, innovation, and interdisciplinary teamwork, ultimately promoting a safer and more resilient future for people everywhere in the face of seismic uncertainty.

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