

Explainable Probabilistic Earthquake Forecasting with Confidence Estimation and Risk Assessment

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Abstract: Earthquake Forecasting remains highly challenging problem because seismic activity is driven by complex and changing patterns, that makes the prediction difficult by using traditional approaches alone. This study proposes an uncertainty aware framework for earthquake magnitude forecasting that combines a hybrid RNN-BiLSTM Attention model with probabilistic forecasting risk assessment and confidence estimation for earthquake magnitude forecasting. The proposed model that integrates three elements First is a Recurrent Neural Network (RNN) for learning sequence, Second Bidirectional Long Short-Term Memory (BiLSTM) for capturing longer-term temporal dependencies, and the third one Attention mechanism focuses on most important information in the earthquake sequences. Historical earthquake record are preprocessed and organized in chronological sequence to forecasting earthquake magnitude across the seven day period.

The proposed model performance is compared with three baseline model that are RNN, LSTM, Transformer models, using three evaluation metrics MSE, MAE, RMSE, R2. The proposed model that is Hybrid RNN-BiLSTM Attention model has given lower MSE(0.1300) and RMSE(0.3606) and the highest R2 (-0.244) among all the evaluated models, and the LSTM model achieved a lower MAE(0.2533). These results prove that the proposed Hybrid architecture provides highly competitive performance across all the evaluation metrics, with offering extra features that baseline model simply lack. To keep the forecast result transparent and easy to understand, Use SHAP technique to make the forecast more understandable by showing which factor has highly influence on the model's prediction.

Keywords: Hybrid RNN-BiLSTM, Earthquake Forecasting, Confidence Assessment, SHAP, Explainable AI

I. INTRODUCTION

Earthquake are the most incredibly destructive natural hazards, causing massive loss of life, infrastructure, and also cause billions in damage, crushing economic damage. Because they are highly influenced by the complex geographical patterns over a time and predicting them accurately becomes most difficult and challenging. Traditional statistical and seismological methods are usefully to study the earthquake, but these methods usually find it difficult to capture the non-linear relationships and temporal dependency in seismic data. Modern Artificial Intelligence and deep learning model such as RNN, BiLSTM, has becomes most highly useful for learning the patterns from the sequential data. These techniques provide a strong and capable methods for forecasting earthquake magnitude using the past historical features such as latitude, longitude, depth, magnitude, time.

However, by just predicting the earthquake magnitude on its own does not indicate why the prediction was made by the model and how it is reliable and how much we can trust it. Sometime deep learning model can be difficult to interpret and the earthquake activity contains considerable uncertainty. Therefore an effective earthquake forecasting system should provide probabilistic Prediction together with explanation, uncertainty, risk and confidence information.



To resolve this need, this study proposes an Explainable Probabilistic Earthquake Forecasting with confidence Estimation and Risk Assessment framework using a proposed model Hybrid RNN-BiLSTM-Attention model. This model learn temporal patterns from past 10 earthquake events or observations and forecast the magnitude over a 7 days horizon. The performance of the proposed model is compared with the baseline model that are RNN, LSTM, Transformer using the metric that are MSE, MAE, RMSE, and R^2 .

To improve the explanation SHAP is used to classify the contribution of each individual input features to predicted magnitude. While we use the Monte Carlo dropout to calculate the how uncertain our prediction is and then use the validation based data to make sure that those confidence are actually accurate. Here the predetermined threshold of ≥ 4.0 is used for risk assessment. Thus, this Architecture provide the forecasted magnitude, important features, uncertainty, confidence, and the risk level, making the forecasting system more transparent and more valuable informative.

II. LITERATURE REVIEW

To make it make better for the earthquake prediction forecasting, the past studies the researcher has explored the Machine learning and Deep learning techniques. These techniques are mainly used to learn the patterns from that past historical data and improve the earthquake forecasting.

Artificial Neural Network:

ANNs are used to learn and understand the difficult and complex pattern and the relationship in the seismic data for the earthquake prediction.

Recurrent Neural Network:

RNNs model is use to analysis or process the data which are in sequential earthquake data and from that learn the temporal patterns for the forecasting.

Transformer:

Transformer is a AI tool model it used to analyze the relationships between the seismic recording and then perform the earthquake forecasting.

III. RESEARCH GAP

Although the existing studies have used the machine learning model and deep learning model such as RNN, ANN, LSTM, BiLSTM, Transformer, etc techniques for the earthquake forecasting, but most of these method and models are mainly focus on prediction performance and uncertainty or explainability but individually or separately. The most current framework cannot integrate the temporal learning, explainability, uncertainty estimation, confidence assessment, risk factor all into one single framework. In addition, predicting the earthquake magnitude alone does not clearly say or indicate that the why this prediction is made by the model itself and how uncertain it is and how risk assessment is reliable. Therefore there is need of integrate approach that combines all the accurate temporal forecasting with the explainability, uncertainty estimation, confidence assessment, risk evaluation.

IV. METHODOLOGY

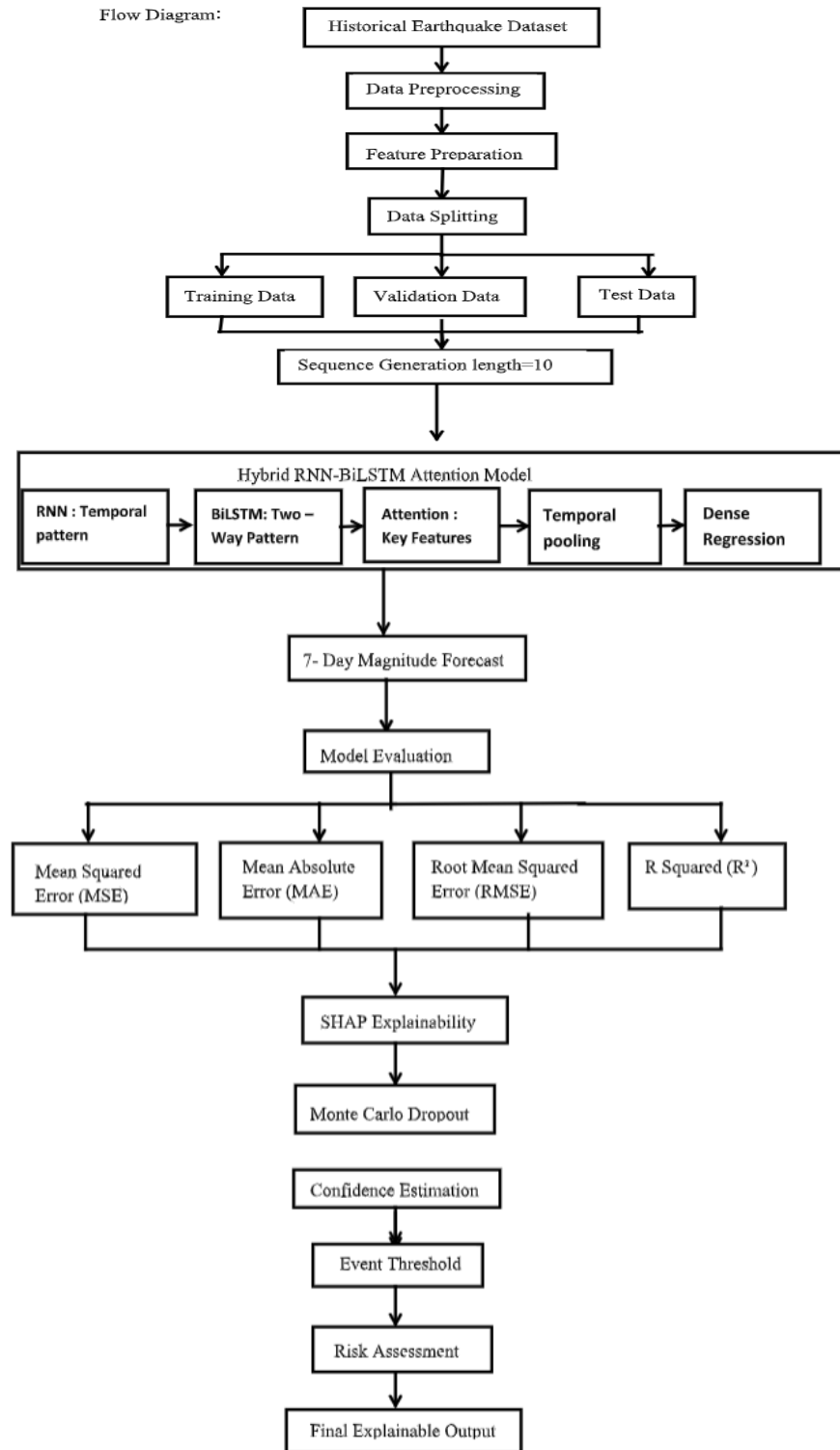
For predicting the earthquake magnitude over a 7 days forecasting horizon. The proposed methodology build an explainable uncertain aware earthquake forecasting framework. The framework preprocesses the past historical earthquake observation data, and then create a temporal sequences from the data and after that applies the propose model Hybrid RNN-BiLSTM Attention model, and provide the output. The methodology consists the following main steps:

Data collection, Data preprocessing, Feature preparation, Data Splitting, Sequence Generation, Hybrid model, Model comparison, Explainability technique, Uncertainty and Confidence, Risk assessment, Final output.

Flow Diagram:



Flow Diagram:



IV. DATASET

For this research project study the dataset is obtained from the United States Geological Survey (USGS) Earthquake Catalog, it contains the historical data of Earthquake data information of the Indian region, and it is publicly available source. The dataset contains the total number is 3,421 earthquake record are available in the dataset and 22 attribute including the Time, Latitude, Longitude, Magnitude, Magnitude type, Location, and other seismic information. The earthquake observation recorded from 2020 to 2026 are there in the dataset.

Data Preprocessing

The original dataset that is obtained from the USGS Earthquake Catalog, very first it is cleaned by removing the invalid or incomplete records, mainly from the important columns such as time latitude, longitude, depth and magnitude. After this the earthquake events were arranged in the chronological order. Specifically from the time field additional temporal feature were extracted such as year, month, day, hour, and the day of the week.

Now for the model training 9 most important feature were selected that are Latitude, Longitude, Depth, Year, Month, Day, Hour, Day of the week. After this the data id been divide into 80% for training, 10 % for validation, and the 10% for testing data. The Numerical feature were standardized by using StandardScaler, apply only on training data so that the data leakage should avoid.

Finally the 10 observation of earthquake events were converted into the input sequence to forecast the earthquake magnitude for 7 day horizon.

Deep Learning Models

There are 3 baseline model and the proposed hybrid model were used fro the earthquake forecasting.

- **RNN** : It is used to learn the sequential and the short – term temporal from the past pervious earthquake observation.
- **LSTM** : It is used to capture long tern dependencies in earthquake sequence and also handle the vanishing – gradient problem from the basic RNN.
- **Transformer** : It is used to capture a relationship between the different observation in sequence using a self attention.
- **Hybrid RNN-BiLSTM Attention** : This proposed model is the combination of the RNN, BiLSTM and the Multi – head Attention it is used to learn the sequential patterns in a two – way temporal dependencies and any important information from the input sequence given.

Algorithm

1. Start
2. Load and clean the dataset collect from the USGS
3. Select the important temporal features
4. Convert the earthquake time into the date time format and extract the temporal features
5. Standardize the all select features and create the sequence of the 10 observation
6. Split the data in chronologically order into training set 80%, validation set 10%, testing set 10%
7. Train the proposed model hybrid RNN – BiLSTM Attention
8. Now use the test data to predict the earthquake magnitude for 7 day horizon
9. Compare and evaluate the model using the matric MAE, MSE, RMSE, R^2
10. Apply SHAP technique for feature explanation and Monte Carlo Dropout is used for the uncertainty and confidence estimation
11. Perform the risk assessment using the magnitude threshold ≥ 4.0
12. Generate the final output showing the predicted magnitude, explanation, uncertainty, confidence, risk level
13. End.



V. MODEL EVALUATION

Mean Squared Error (MSE) : MSE is used to measure the average squared difference between the actual and the predicted earthquake magnitude and it also give importance to the lager prediction error

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

2. Mean Absolute Error (MAE) : MAE show the average absolute difference between the actual and the predicted earthquake magnitude it also provide an easy to understand measure prediction error

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

3. Root Mean Squared Error (RMSE) : RMSE is used to measure the typical prediction error and express it in the same unit as the earthquake magnitude it gives more weight to larger error

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

4. Coefficient and Determination (R^2) : It shows the how well the model is explaining the variation in earthquake magnitude. In this a higher value means a better performance.

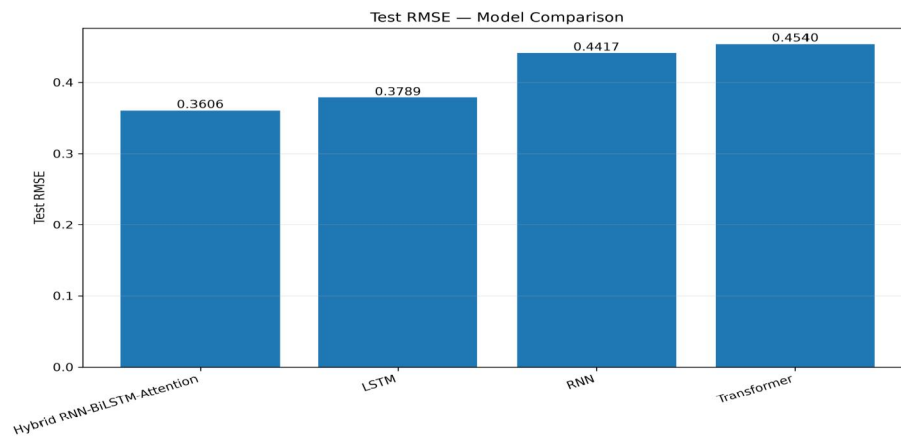
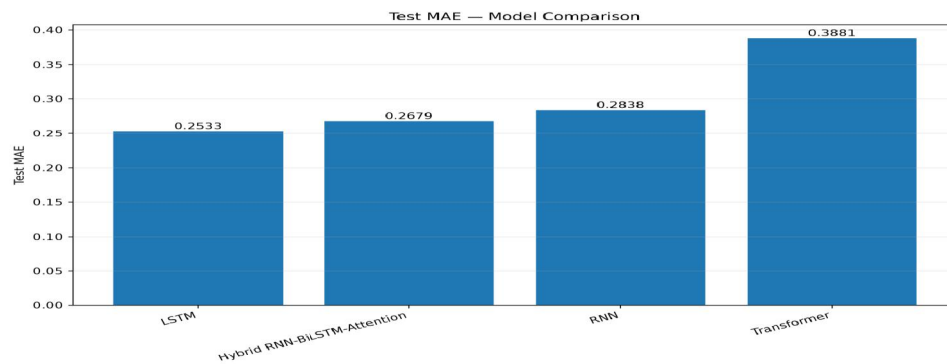
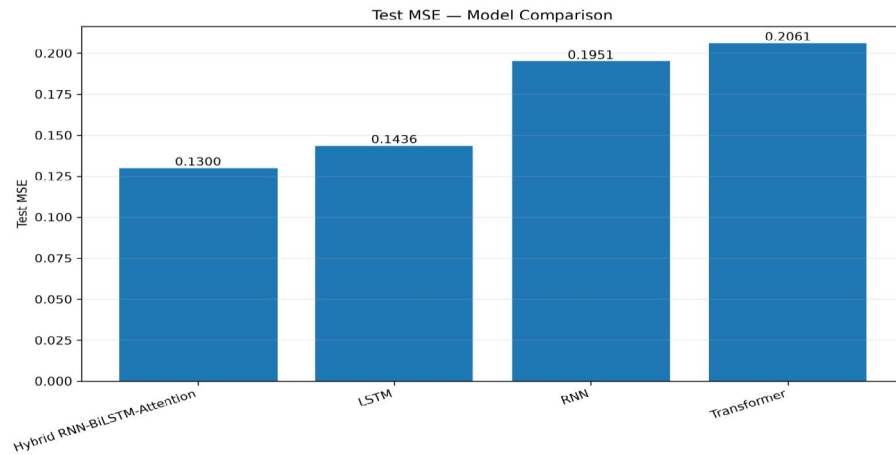
$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

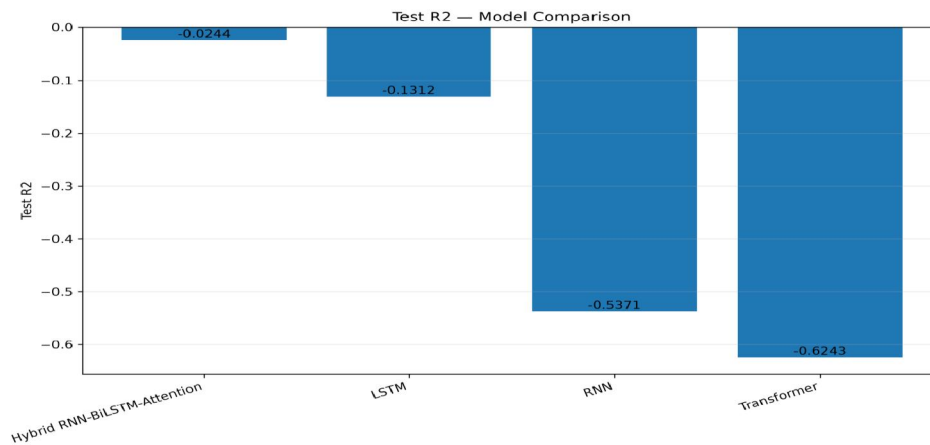
VI. FINDING AND RESULT

After the model training and testing the result of all three model are:

Model	MSE	MAE	RMSE	R^2
RNN	0.1951	0.2838	0.4417	-0.5371
LSTM	0.1436	0.2533	0.3789	-0.1312
Transformer	0.2061	0.3881	0.4540	-0.6243
Hybrid model RNN- BiLSTM Attention	0.1300	0.2679	0.3606	-0.2244







VII. MAJOR FINDING

The major findings from this proposed earthquake forecasting research study are as follow:

1. The proposed model Hybrid RNN – BiLSTM Attention model has achieved the lower MSE and RMSE among all other models.
2. The combination of the RNN, BiLSTM, Attention has help to capture the important temporal pattern from the earthquake sequence
3. The explainability SHAP technique help to show which feature has affected the predict the earthquake forecasting magnitude.
4. Mont Carlo help to understand the how estimate how uncertain the predict was.
5. The model provide the confidence along with prediction.
6. The model provide confidence estimation along with the perdition
7. The magnitude 4.0 or above was used to select threshold for the risk assessment.
8. The overall finding is that the framework has the combination of all prediction, explanation, uncertainty, confidence and the risk in one system .

VIII. LIMITATION

The limitation of the proposed earthquake forecasting framework is that the dataset contains limited number earthquake observation record the model use only the selected seismic and the temporal feature so some of the geographical and environment factors is not include. The model predict earthquake magnitude for 7 days forecasting horizon but does not exact time and location. The use of past observation may also miss the longer term pattern the values of uncertainty and confidence are model based estimate while the SHAP explain the feature contribution but don't shoe the causation. The magnitude ≥ 4.4 thershold is a project defined and should not be treated as the universal danger level.

IX. CONCLUSION

This research study presented an explainable uncertainty aware earthquake forecasting framework using a hybrid model that is hybrid RNN-BiLSTMAAttention model for 7 day magnitude forecasting horizon The proposed HYbride mmodel has achieved the lowest MSE(0.1300) and the lowest RMSE(0.3606) among all the evaluated model while the LSTM has achieve lower MAE(0.2533).

The framework use the SHAP technique to explain the feature contribution and the Monte Carlo Dropout is used to predicted the uncertainty and confidence . A predefined magnitude tshershold is 4.0 is also used for the risk assessment.



Overall the study show that the combining all forecasting, explainability, confidence, uncertainty, and the risk and provide a more informative framework than only doing prediction alone

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