Performance analysis of machine learning and deep learning architecture for earthquake magnitude prediction

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***Abstract*—Earthquakes possess immense destructive power, capable of causing significant harm to buildings and the natural surroundings. Accurate earthquake magnitude prediction is crucial for determining seismic risks and implementing appropriate mitigation measures. Although deep learning (DL) and machine learning (ML) algorithms have been utilized extensively in earthquake prediction research, a thorough DL vs. ML comparison is absent. The comparison is broadened in this research by concentrating on earthquake magnitude prediction. Moreover, we employ a set of innovative algorithms that have had limited application within this domain. The optimal algorithm to estimate the magnitude of an earthquake has not been explicitly discussed in any of the papers. This study aims to bridge this gap by employing a diverse range of twelve algorithms, i.e. Decision Tree Regressor, Random Forest Regressor, SVR, Linear Regressor, Gradient Boosting, XGBoost, LightGBM, CatBoost, ANN, RNN, LSTM, and MLP, encompassing both machine learning and deep learning techniques, to predict earthquake magnitudes. Through comprehensive experimentation and comparative research, we evaluate the performance of the ensemble-based models in terms of different evaluation metrics, such as R^2 Scores, MAE, MSE and RMSE.**

***Index Terms*—Machine learning, Deep learning, Earthquake magnitude**

I. Introduction

An earthquake is a sudden release of energy in the Earth's crust brought on by the movement of tectonic plates, which causes the ground to shake or vibrate. Magnitude measures the size or intensity of an earthquake, representing the energy released at its source, usually expressed on a logarithmic scale like the Richter scale or moment magnitude scale. In 1935, Charles F. Richter introduced the Richter scale, also known as the local (M_L) magnitude scale, to measure earthquakes [15]. Subsequently, several studies have proposed different types of magnitude scales.

Earthquakes are incredibly destructive, capable of causing significant harm to both man-made structures and the surrounding natural environment. It is essential to comprehend the basic root causes of earthquakes and create accurate prediction models to lessen their effects. With the use of machine learning (ML) algorithms, it is possible to examine intricate connections and patterns in earthquake data and make precise forecasts. Additionally, deep learning (DL) algorithms can offer essential insights into the behavior of seismic occurrences due to their capacity to record complex relationships.

Various techniques have been used in numerous pieces of research to predict earthquake magnitudes. Researchers have already implemented algorithms such as Random Forest Regressor, SVR, MLP [5], ANN [11], CNN [7], and numerous other algorithms explored in the field. Compared to other methods, machine learning algorithms are less frequently used to predict the magnitude of earthquakes. This study uses a wide range of algorithms, including both machine learning and deep learning techniques, to investigate the prediction of earthquake magnitude. Below is a list of this paper's notable contributions:

1) The effectiveness of DL models and ML models in forecasting earthquake magnitudes has been thoroughly compared.
2) Implementing Gradient Boosting, XGBoost, LightGBM, and Catboost algorithms to predict earthquake magnitude.

The structure of this paper is as follows: A thorough analysis of the pertinent literature on earthquake magnitude prediction is provided in Section II. We detail the dataset used for this investigation in Section III and present the approaches used. The comprehensive findings and performance analysis of the implemented algorithms are shown in Section IV. The report is finally concluded in Section V with a summary of the major findings and recommendations for additional research.

II. Literature Review

In recent times, several studies have explored the use of deep learning on raw seismic waveforms to quickly assess earthquake parameters. These parameters encompass magnitude estimation [10], location determination [8], and peak ground acceleration analysis [6]. H. Adeli et al. devised a probabilistic neural network specifically for earthquake prediction within a specific region. Their model was trained using eight earthquake indicators and exhibited promising results for earthquakes ranging from magnitudes 4.0 to 6.0 [2]. In 2018, Perol et al. introduced ConvNetQuake, a specialized Convolutional Neural Network (CNN) designed to detect and precisely locate microseismic earthquakes using waveform data from a single station [14]. Negarestani et al. utilized a Back Propagation Neural Network (BPNN) in 2002 to identify abnormal patterns in radon concentration caused by earthquakes [12]. Liu et al. employed a combination of Radial Basis Function (RBF) neural networks in 2004 to forecast earthquakes in China, utilizing historical earthquake magnitude data as input [9]. In 2007, Panakkat and Adeli introduced a novel technique for earthquake prediction in Southern California and the San Francisco Bay areas, based on mathematical seismic indicators derived from the temporal distribution of recorded seismic events. Their method involved monthly predictions using Artificial Neural Networks (ANNs) to model the correlation between earthquake occurrences and identified parameters [13]. An artificial neural network utilizing earthquake predictors has been proposed to predict medium-large magnitude earthquakes in Tokyo [4]. Zamani et al. (2013) proposed a hybrid approach integrating neural networks and fuzzy logic for earthquake forecasting in Iran [17]. Wang (2001) proposed a neural network model employing a single multi-layer perceptron to estimate earthquakes in Mainland China [16]. Furthermore, a multi-layer perceptron neural network was employed to predict earthquakes using time series data of total electron content (TEC) [3]. In another study, earthquake magnitude was predicted using latitude, longitude, and depth as input variables. The models used were MLP, SVR, and Random Forest Regression. [5]

Research Gap: From the existing body of knowledge, three notable research gaps can be identified. *Firstly*, there has been a limited emphasis on conducting performance analysis of machine learning and deep learning models for the prediction of earthquake magnitude. *Secondly*, there is an inadequate comparison of the effectiveness of deep learning (DL) models and machine learning (ML) models in forecasting earthquake magnitudes. *Thirdly*, limited exploration of Gradient Boosting, XGBoost, LightGBM, and Catboost algorithms for earthquake magnitude prediction.

III. Methodology

The methodology used in our study will be covered in this section, with a focus on both machine learning and deep learning techniques. We wanted to thoroughly look into and evaluate the performance of various algorithms for our research goals by incorporating them.

A. Dataset

We used a dataset with 23,413 instances that were made accessible on Kaggle for our study [1]. The dataset, which includes the years 1965 to 2016, is focused on seismic occurrences that were reported to have a magnitude of 5.5 or greater. There are a total of 21 columns that provide different types of information. We only focused our investigation on the four relevant columns, though. Latitude, Longitude, and Depth are the chosen characteristics, while Magnitude is the desired variable. By taking into account these particular characteristics, we sought to study the link between geographical coordinates (Latitude and Longitude) and depth with the magnitude of seismic events reported in the dataset. A sample dataset from the data used to estimate earthquake magnitude is shown in Table I. The associations between all potential pairs of the earthquake magnitude prediction factors are shown by the distribution and correlation graphs in Figure 1. The correlation matrix in Figure 2 also uses a seaborn heatmap to display the relationships between the earthquake magnitude prediction data factors on a scale from 0 to 1.

TABLE I
SAMPLE DATASET

Serial no.	Latitude	Longitude	Depth	Magnitude
1	19.246	145.616	131.6	6
2	1.863	127.352	80	5.8
3	-20.579	-173.972	20	6.2
4	-59.076	-23.557	15	5.8
5	11.938	126.427	15	5.8

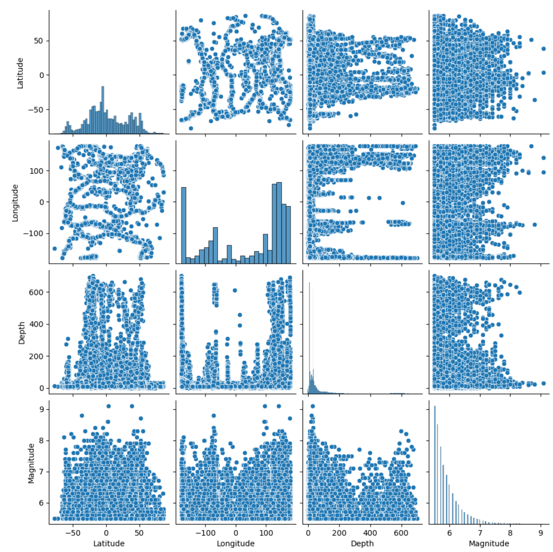

Fig. 1. Pairwise Distribution and Correlation Plots of Earthquake Magnitude Prediction Data

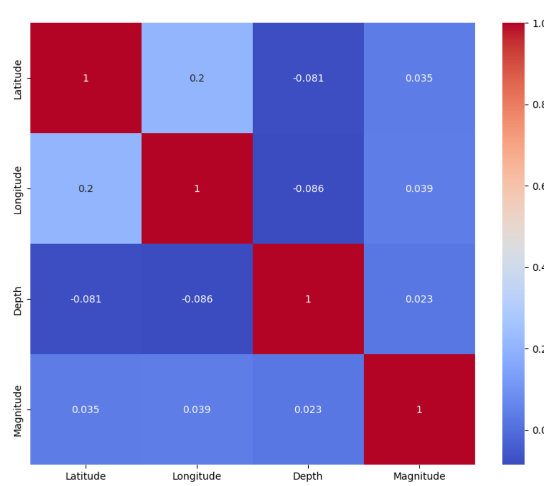

Fig. 2. Seaborn Heatmap of Correlation Matrix (Scale: 0 to 1)

B. Proposed Framework Using Machine Learning

The methodology for predicting magnitude using machine learning is shown in Figure 3. Data collection and preprocessing come first in the process. Then, feature selection is carried out to determine which factors are most important. The model is then trained using the chosen features to allow for magnitude prediction.
Algorithm 1 outlines the pseudocode for utilizing machine learning to predict earthquake magnitude.

Algorithm 1 Earthquake Magnitude Prediction Using Machine Learning

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Input: Longitude, Latitude and Depth
Output: Magnitude Prediction and Error Values
Step 1: Retrieve the dataset containing Earthquake Magnitude
Step 2: Perform feature selection by identifying and selecting the dataset's most relevant features.
Step 3: Perform data cleaning by removing incorrect, corrupted, incorrectly formatted, duplicate, or incomplete data within the dataset.
Step 4: Split the dataset into 80% for training and 20% for testing purposes.
Step 5: Train different ensemble machine learning models using the dataset.
Step 6: Calculate three distinct error values, E_{R^2}, E_{MAE}, and E_{MSE} for every model.

C. Machine Learning Methods for Predicting Earthquake Magnitude

Machine learning is a powerful technique that enables machines to learn automatically. This method allows for the training of machines utilizing enormous volumes of data, and after training, these machines are capable of making decisions on their own. We used eight different machine learning algorithms in our research. We will briefly describe each algorithm and highlight its unique functions and importance in our study in the following subsection.

- Decision Tree Regressor(DT): A machine learning technique, Decision Tree Regressor, is used for regression tasks. Recursively dividing the feature space, it builds a tree-like structure that links features to the target variables. Because of this, the model can predict continuous values, which makes it ideal for regression tasks.
- Random Forest Regressor(RF): An ensemble learning technique, Random Forest Regressor, combines different learning algorithms to increase prediction accuracy. During training, it creates several decision trees and combines their predictions to produce outputs that are more accurate and trustworthy.
- Linear Regressor: A popular machine learning technique for forecasting continuous numerical values is linear regression. It looks for the line that fits the data the best and minimizes the discrepancy between the expected and actual values. It gauges the influence of each feature on the target variable by estimating coefficients for each feature.
- Support Vector Regressor (SVR): An efficient machine learning method for regression tasks is called the SVR. It looks for a hyperplane that precisely fits the training data while maximizing the margin around it. SVR, in contrast to conventional regression techniques, has a tolerance margin, allowing for some predictability. Due to its adaptability, SVR is capable of handling outliers and complex datasets.
- Gradient Boosting: By combining weak prediction models, gradient boosting produces a robust and precise model. It creates an accurate final model by fixing mistakes introduced by earlier models. Gradient boosting increases prediction accuracy across industries due to its adaptability in addressing complicated situations and a variety of inputs.
- Extreme Gradient Boosting (XGBoost): An effective machine learning method with strong prediction capabilities is called XGBoost. It can handle complicated datasets and capture subtle patterns since it blends gradient boosting with cutting-edge algorithms. XGBoost avoids overfitting and speeds up training with parallel processing and regularisation techniques. Classification, regression, ranking, and recommendation systems all use it.
- Light Gradient Boosting Machine (LightGBM): Modern gradient-boosting framework LightGBM excels in terms of speed, potency, and precision. It effectively manages challenging problems and massive datasets using a "leaf-wise" tree growth approach, producing highly optimized models.
- CatBoost: CatBoost is a very effective gradient-boosting method created specifically for categorical data. It is suitable for real-world datasets since it does not require human encoding or feature engineering. CatBoost covers both classification and regression problems and effectively handles missing variables. It finds applications in a variety of sectors because of its high learning capabilities.

D. Proposed Framework Using Deep Learning

The framework of predicting earthquake magnitude using deep learning is illustrated in Figure 4. Similar to machine learning techniques, the initial step involves extracting and storing the data in a CSV file. Subsequently, feature selection is performed. Notably, data cleaning is unnecessary as deep learning models handle that automatically. The data is then divided into two sets: 80% for training and 20% for testing. Finally, the deep learning model is trained, and the results are evaluated using the test data.
Algorithm 2, describes the procedure for predicting earthquake magnitude using deep learning techniques.

E. Deep Learning Methods for Predicting Earthquake Magnitude

Deep learning is an area of artificial intelligence that focuses on training neural networks with numerous layers to recognize

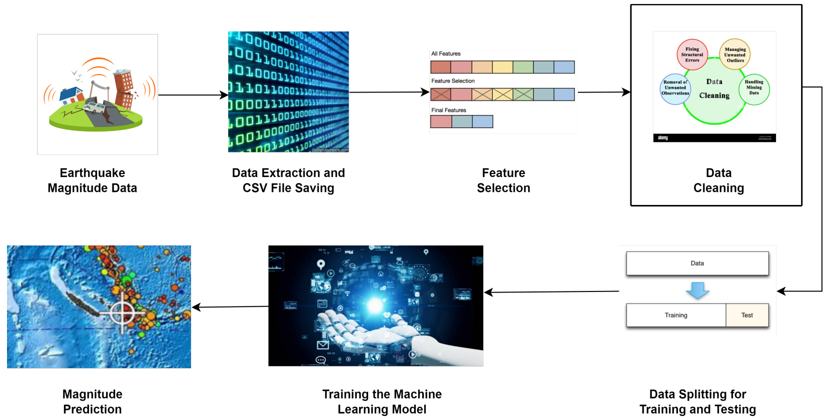

Fig. 3. Framework for Magnitude Prediction Using Machine Learning

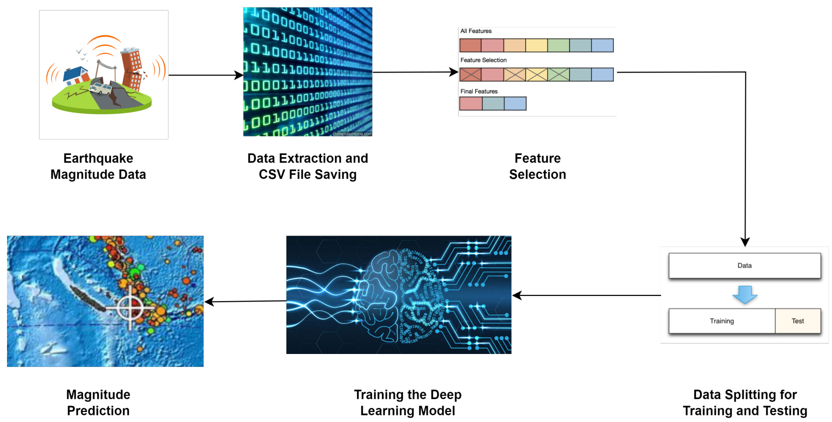

Fig. 4. Framework for Magnitude Prediction Using Deep Learning

Algorithm 2 Earthquake Magnitude Prediction Using Deep Learning

Input: Longitude, Latitude and Depth
Output: Magnitude Prediction and Error Values
Step 1: Retrieve the dataset containing Earthquake Magnitude.
Step 2: Perform feature selection by identifying and selecting the dataset's most relevant features.
Step 3: Split the dataset into 80% for training and 20% for testing purposes.
Step 4: Train different ensemble deep learning models using the dataset.
Step 5: Calculate three distinct error values, E_{R^2}, E_{MAE}, and E_{MSE} for every model.

patterns and make predictions or decisions. It takes inspiration from how the human brain works structurally and functionally, where interconnected neurons process information. Within this subsection, we have employed four distinct deep-learning algorithms. We will provide a concise overview of each of these algorithms in this subsection.

- Artificial Neural Networks (ANN): ANN is superior at pattern extraction, image recognition, and natural language processing because they closely resemble the human brain. They accommodate for adaptation through weight and bias changes, but careful design is needed to avoid overfitting.
- Recurrent Neural Networks (RNN): By using feedback connections to recall and utilize prior information, RNNs analyze sequential data. Due to their capacity to recognize temporal connections, they excel in tasks like natural language processing, speech recognition, and time series analysis.
- Long Short-Term Memory (LSTM): The vanishing gradient problem is handled by the LSTM, a specialized RNN that also detects long-term dependencies in sequential data. Deep neural network training is made robust and effective by LSTMs, which use memory cells and gating mechanisms to selectively preserve and update information while controlling data flow.
- Multi-Layer Perceptron (MLP): MLP, a vital deep learning technique, employs multiple layers of interconnected artificial neurons. It is commonly utilized for regression and classification tasks and excels in estimating nonlinear functions. Neurons perform a weighted sum, incorporate

a bias term, and apply an activation function to the result. With its nonlinearity, the MLP network can effectively learn and represent complex relationships in the data.

IV. Experimental Result

A. Performance Analysis of Machine Learning Models

Table II summarizes the evaluation metrics for embedded machine learning algorithms. Linear regression showed poor predictive power with low R^2, moderate MAE, MSE, and low RMSE. SVR performed slightly better but still had negative R^2 and relatively high error metrics. Decision Tree and Random Forest models did poorly. Gradient Boosting showed improved performance with positive R^2 and decreased error metrics, indicating increased precision. XGBoost, LightGBM, and CatBoost achieved positive R^2 and low error metrics, demonstrating high prediction accuracy. Figure 5 illustrates a comparison of evaluation metrics for the above-mentioned models.

TABLE II
Performance Metrics of ML Models

Models	Evaluation Metrics			
	R^2 Scores	MAE	MSE	RMSE
Decision Tree Regressor	-0.88427	0.409999	0.347547	0.589532
Random Forest Regressor	-0.0874481	0.32568	0.200576	0.447857
Linear Regressor	-0.000941499	0.315503	0.18462	0.429675
SVR	-0.0661678	0.296007	0.196651	0.443454
Gradient Boosting	0.032961	0.308546	0.178367	0.422335
XGBoost	0.0327352	0.308506	0.178409	0.422385
LightGBM	0.0324057	0.308683	0.17847	0.422457
CatBoost	0.0313326	0.308885	0.178668	0.422691

B. Comparing Predictions with Actual Data of Machine Learning Models

Table III shows a comparison between the observed magnitudes and those predicted by several machine learning models. Utilizing the provided dataset, each model was trained and assessed. Upon closer examination of the provided table, we can see how the various models' expected and actual magnitudes differ from one another.

TABLE III
Predicted vs Actual Magnitude Values of ML Models

Actual Value	DT	RF	Linear Regressor	SVR	Gradient Boosting	XGBoost	LightGBM	CatBoost
5.6	5.6	5.6	5.8	5.7	5.8	5.8	5.8	5.8
6	6	5.6	6	5.8	6	6	6	5.9
6.6	5.8	6.4	6	5.8	5.9	5.9	5.9	5.9
7.8	7.8	7.07	6	5.7	5.8	5.8	5.9	5.9
5.7	5.7	5.7	5.8	5.7	5.8	5.8	5.8	5.8

C. Performance Analysis of Deep Learning Models

Table IV presents the performance metrics of the deep learning models. RNN appears to perform somewhat better than other models in terms of R^2 score and error metrics,

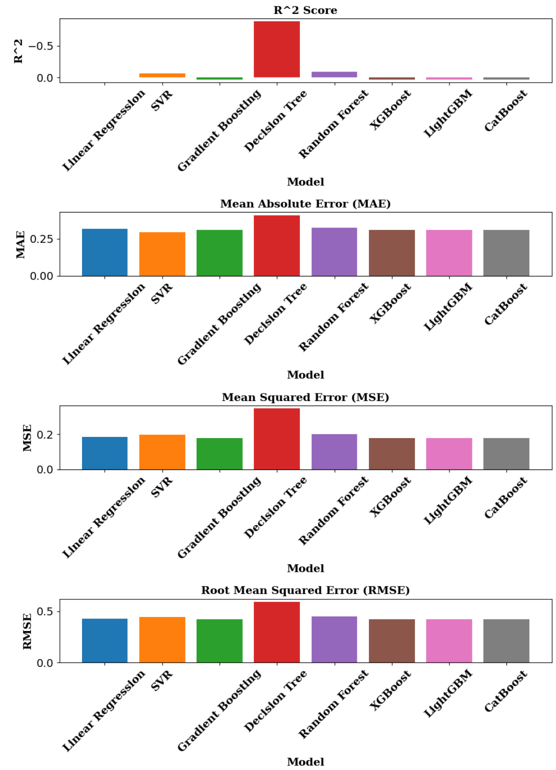

Fig. 5. Bar Chart of Performance Metrics for Machine Learning Models

according to the presented metrics. In comparison to the other models, it has a significantly higher R^2 score and somewhat lower MAE, MSE, and RMSE values. Even though the ANN model has a negative R^2 value, its prediction errors are rather small. Like ANN and RNN, LSTM exhibits minimal prediction errors, but it too faces the problem of a negative R^2, which denotes a poor fit. The MLP model, on the other hand, has the most prediction errors and the lowest R^2 rating. Figure 6 provides a visual comparison of the evaluation metrics for the models mentioned earlier.

TABLE IV
Performance Metrics of DL Models

Models	Evaluation Metrics			
	R^2 Scores	MAE	MSE	RMSE
ANN	-0.0423799	0.298671	0.192264	0.438479
RNN	0.000‘801941	0.315256	0.184299	0.4293
LSTM	-0.0640533	0.29505	0.196261	0.443014
MLP	-0.102661	0.351232	0.203382	0.450979

D. Comparing Predictions with Actual Data of Deep Learning Models

Table V displays the actual and anticipated magnitudes of multiple deep learning models, it is clear that each model displays distinctive performance traits. The comparison of the predicted and actual magnitudes reveals important information about how well these models are able to identify the fundamental patterns and trends in the data.

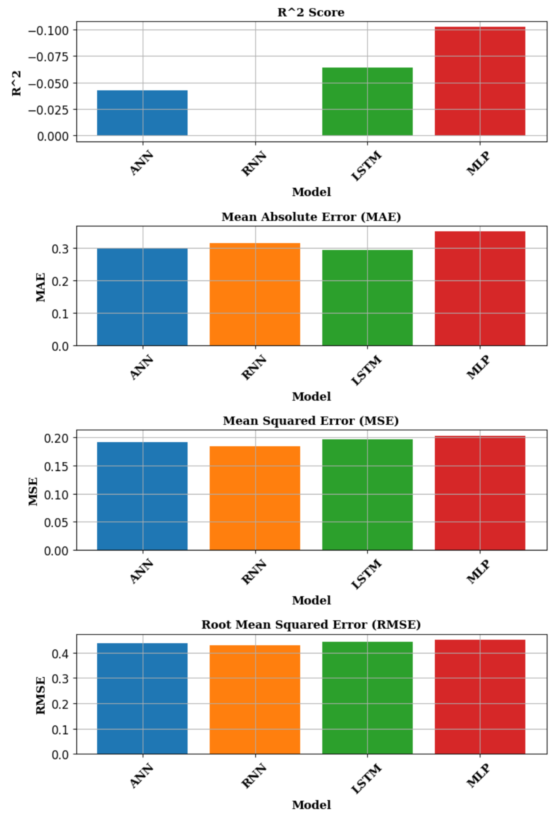

Fig. 6. Bar Chart of Performance Metrics for Deep Learning Models

TABLE V
PREDICTED VS ACTUAL MAGNITUDE VALUES OF DL MODELS

Actual Value	ANN	RNN	LSTM	MLP
5.6	5.9	5.8	5.7	5.8
6	5.7	5.8	5.8	6
6.6	5.9	5.8	5.7	5.9
7.8	5.9	5.8	5.7	6
5.7	5.7	5.8	5.7	6

V. CONCLUSION

Due to the potentially disastrous effects, they may have on people, infrastructure, and communities, earthquake prediction is of the utmost importance. In order to predict earthquake magnitudes, a combination of eight machine learning algorithms and four deep learning algorithms was used in this study. We may assess the estimated error values to evaluate how well the algorithm predicts magnitudes. RNN outperformed the other deep learning models on a comparative basis. But XGBoost, LightGBM, and CatBoost all showed positive R^2 values and relatively low error metrics which indicates high prediction accuracy than other models. These machine learning models show a remarkable aptitude for capturing the data's variability, leading to precise predictions. By offering information on how various ML and DL models perform, this research advances the field of earthquake magnitude prediction. The findings can help direct future studies and contribute to the creation of prediction models that are more precise, ultimately improving seismic event early warning systems and preparedness measures.

Future research could focus on improving earthquake magnitude prediction by using ensemble methods from machine learning and deep learning. Additionally, exploring the effects of additional features or data sources, like seismic patterns and geological properties could enhance forecasting. The development of an AutoML tool for versatile dataset predictions is also worth considering.

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