

Data-Driven Prediction of Earthquake Parameters Using Historical Seismic Records and Machine Learning

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Abstract

Earthquakes are considered to be among the most devastating natural disasters, which often lead to serious human impacts and economic imbalance. Despite the scientific impossibility in taking an accurate forecast of earthquake occurrence, machine learning has advanced in the calculation of most important seismic parameters hence disaster preparedness and reduction. This paper performs a comparative analysis of machine learning models involved in predicting the magnitude, and depth of earthquakes, which contain the acquired historical seismic data provided by United States Geological Survey (USGS) between the analysis period (1965-2016). The refined data set, containing more than 23,000 events tagged with data described as latitude, longitude, depth, and magnitude underwent the data cleansing process to remove errors and out Within the data clean-up process of the dataset, feature engineering was applied so as to make the data more predictive. Several models, specifically Polynomial Regression, random Forest Regressor, Linear Regression, and (LSTM) networks were trained and had been analysed based on statistical metrics such as the coefficient of determination (R^2), mean squared error (MSE), and explained variance. Experiment findings have shown that Polynomial Regression could achieve high magnitude prediction ($R^2= 0.92$, $MSE = 0.0341$) and the random forest regressor with the highest accuracy of depth prediction ($R^2= 0.85$). On the other hand, the LSTM model failed to perform as high as possible, which can be attributed to the fact that it is not a truly sequential dataset. These findings highlight the applicability of hybrid modeling to the prediction of earthquakes to offer the benefits of data-driven information, which can be used to inform early warning systems, city planning, and risk management. A different extension of the current study can be the incorporation of real-time seismic data, Geographic Information Systems (GIS), and advanced deep learning architectures to improve time and space modeling.

Keywords: AI, Earthquake prediction, Machine learning, Seismic data analysis, Random Forest, Polynomial Regression, Disaster management.

1. INTRODUCTION

The Earthquakes are among the most devastating natural phenomena, capable of inflicting massive destruction on infrastructure, causing significant economic losses, and leading to large-scale casualties. Despite decades of scientific progress, precise earthquake prediction in terms of time, location, and magnitude remains an unsolved challenge in geoscience [1]. Conventional seismological methods rely primarily on statistical models and physical simulations of tectonic processes, but these approaches struggle to capture the highly complex, non-linear nature of seismic activity. Consequently, there is growing interest in exploring artificial intelligence (AI) and machine learning (ML) as data-driven alternatives to improve predictive modeling of earthquake characteristics. Machine learning methods have the ability to discover hidden patterns within large-scale datasets, making them particularly suitable for analyzing seismic data. Attributes such as latitude, longitude, depth, and magnitude can be leveraged to build predictive models that, while not capable of determining the exact time of an earthquake, can provide valuable estimates of its severity and depth. Such predictive insights have a direct impact on disaster preparedness, risk management, and urban planning, particularly in high-risk

seismic zones. Early warning systems are crucial in disaster management, as they help mitigate the risk of casualties and reduce economic disruption. Machine learning (ML) methods have increasingly been explored for this purpose, offering new possibilities in earthquake prediction.

Ensemble learning techniques, such as Random Forest, have proven effective at modeling complex non-linear patterns in seismic datasets while reducing overfitting and enhancing generalization performance [3]. Deep learning models, particularly (LSTM) networks, have been utilized to capture sequential dependencies in temporal seismic data streams [6] [9]. More recently, hybrid frameworks, including CNN–LSTM combinations and transformer-based models, have demonstrated improved predictive power by integrating spatial and temporal features [15] [16]. Nevertheless, a critical challenge persists in identifying models that can simultaneously balance accuracy, interpretability, and computational efficiency when applied to heterogeneous seismic datasets spanning multiple decades and diverse regions. Building on this research landscape, the present study performs a comparative assessment of multiple ML algorithms for earthquake parameter prediction. Using historical seismic data from the United States Geological Survey (USGS) covering 1965–2016, four models—Polynomial Regression, Random Forest Regressor, Linear Regression, and LSTM neural networks—were implemented. The dataset, comprising more than 23,000 global earthquake records, underwent rigorous preprocessing to address missing values, eliminate outliers, and normalize key features. Feature engineering was also employed to highlight critical seismic parameters. Model performance was evaluated using widely accepted statistical metrics, including the coefficient of determination (R^2), Mean Squared Error (MSE), and Explained Variance. The findings indicate that Polynomial Regression achieved the best results for magnitude prediction ($R^2= 0.92$, $MSE = 0.0341$), while Random Forest Regressor provided the highest accuracy for depth prediction ($R^2= 0.85$), underscoring its strength in modeling complex feature interactions. Conversely, LSTM exhibited relatively poor performance due to the dataset's lack of sequential continuity, highlighting the limitations of deep learning when applied to non-temporal data. These results suggest that while deep learning holds promise in seismic applications, classical regression and ensemble methods remain competitive and, in some cases, superior for specific prediction tasks. The contributions of this research are threefold: (i) it offers a systematic comparison of regression, ensemble, and deep learning techniques for earthquake prediction, (ii) it identifies Polynomial Regression as a highly effective yet lightweight approach for magnitude estimation, and (iii) it demonstrates the robustness of Random Forest in predicting earthquake depth, thereby providing practical insights for the design of data-driven seismic risk assessment frameworks. Second, it highlights the underexplored potential of Polynomial Regression for modeling non-linear seismic patterns, positioning it as a promising alternative to conventional linear models. Third, it underscores the applicability of Random Forests in depth prediction, where feature interactions play a dominant role. Together, these insights extend the understanding of how different ML models can be tailored for specific predictive tasks in earthquake analysis. The remainder of this paper is organized as follows. Section 3 defines the problem statement and highlights the research gap addressed in this work. Section 4 describes the dataset, preprocessing techniques, feature engineering, and the machine learning models employed. Section 5 presents the experimental setup, evaluation metrics, and the comparative results of different models. Section 6 discusses the key findings in the context of existing literature and provides practical implications. Finally, Section 7 concludes the study and outlines future research directions.

2. DISCUSSION ON LITERATURE SURVEY

The prediction of earthquakes has been a longstanding challenge in geoscience, attracting significant research interest across statistical, physical, and computational domains. Early studies emphasized the theoretical limitations of earthquake prediction, with Geller et al. [1] arguing that precise forecasts of

time and location were scientifically unattainable given the complexity of tectonic processes. Reasenber and Jones [2] further highlighted the uncertainties involved in aftershock forecasting, underscoring the need for probabilistic rather than deterministic approaches. With the rise of machine learning, researchers began to apply data driven methods to earthquake prediction tasks. Breiman's introduction of the Random Forest (RF) algorithm [3] provided a robust ensemble method capable of handling non-linear patterns and noisy datasets. Subsequent works leveraged RF to improve the classification of seismic events into major and minor categories, as demonstrated by Mallouh et al. [7]. Regression-based methods were also investigated; for example, Li and King (2009) explored polynomial regression combined with k-nearest neighbor (PR-KNN) to improve aftershock prediction, while Asim et al. [5] reported that a Probabilistic Recurrent Neural Network (PRNN) achieved 65% accuracy in magnitude forecasting in the Hindukush region. Deep learning approaches have gained traction in the last decade, particularly with the application of neural networks to seismic data. Srivastava et al. [4] introduced dropout regularization to address overfitting in deep models, a technique later adopted in seismic prediction tasks. Kuyuk and Susumu [6] demonstrated the use of (LSTM) networks for real-time earthquake recognition, showing that deep architectures could exploit temporal dependencies in seismic sequences. Similarly, Bhandarkar et al. [8] compared LSTM with feedforward neural networks and reported superior performance of LSTM for trend prediction. Perol et al. [9] employed convolutional neural networks (CNNs) for earthquake detection and location, while Musabi et al. [10] introduced transformer-based models for simultaneous earthquake recognition and seismic phase picking, marking a shift towards more advanced architectures. Recent studies (2020–2024) have expanded these efforts by integrating hybrid and spatio-temporal models. Xu et al. [14] proposed hybrid deep learning frameworks that combined CNN and RNN layers for improved predictive accuracy. Wang et al. [15] developed a CNN–LSTM model tailored for sequential seismic data, achieving strong performance in magnitude forecasting. Li et al. [16] introduced transformer-based neural networks that incorporated spatial and temporal representations, outperforming traditional models in certain prediction tasks. Beyond model architectures, Rahman et al. [17] provided a systematic review of ML approaches for seismic risk assessment. The literature indicates a clear progression from theoretical scepticism to applied machine learning and deep learning methods for earthquake prediction. While ensemble learning and regression methods continue to offer competitive performance for specific tasks such as depth and magnitude estimation, the frontier of research increasingly lies in hybrid architectures and real-time system integration. This motivates our study, which benchmarks classical, ensemble, and deep learning models on a large USGS dataset, thereby providing insights into their relative strengths for magnitude and depth prediction tasks. For reference of technology growing over the years refer to the Figure 1.

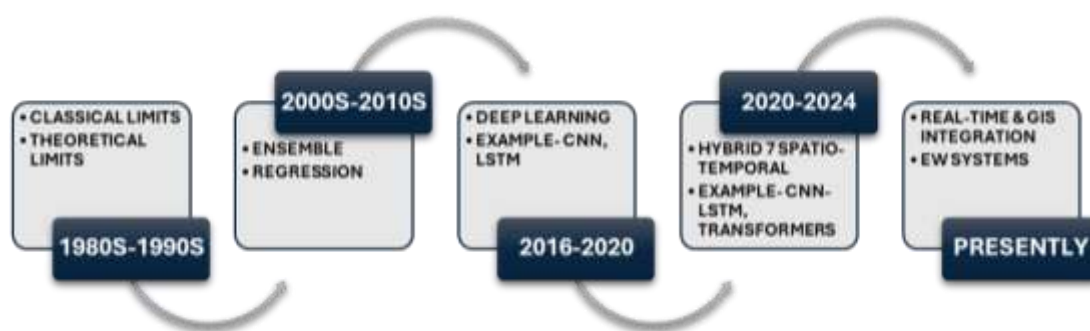


Fig. 1: Two-row summary of literature evolution in earthquake prediction.

3. PROBLEM STATEMENT

Earthquakes remain one of the most destructive natural hazards, yet their occurrence is highly unpredictable due to the non-linear and complex nature of seismic activity. Existing seismological models rely heavily on physical simulations and statistical laws, which provide probabilistic assessments but lack the ability to accurately forecast key earthquake parameters. Precise prediction of time and location remains scientifically infeasible [1], but estimating critical parameters such as magnitude and depth can significantly improve early warning systems, disaster preparedness, and risk management.

Machine learning techniques offer a promising alternative, as they can capture hidden correlations in large-scale seismic datasets. However, challenges remain in identifying suitable algorithms that balance accuracy, interpretability, and computational efficiency. For instance, ensemble methods like Random Forests excel at handling non-linear feature interactions but may overfit small datasets. Regression techniques can model continuous parameters but often fail to capture complex patterns. Deep learning models such as LSTMs exploit temporal dependencies but may perform poorly when the dataset lacks sequential consistency. The problem addressed in this study is therefore defined as follows:

How can machine learning models be effectively employed to predict earthquake magnitude and depth from historical seismic data, and which algorithms are most suitable for capturing the non-linear and spatial dependencies inherent in such datasets?

This formulation emphasizes the dual objective of (i) predicting earthquake parameters with high reliability, and (ii) comparing multiple machine learning models to identify the most effective approaches for seismic risk estimation.

4. METHODOLOGY

This section outlines the methodology followed in developing and evaluating machine learning models for earthquake prediction. The process consists of five major stages: dataset acquisition, data preprocessing, feature engineering, model training, and model evaluation. Figure 2 provides an overview of the workflow.

4.1 Dataset Description

The dataset used in this study was obtained from the United States Geological Survey (USGS), covering global earthquake events between 1965 and 2016. It comprises more than 23,000 records, each containing attributes such as date, time, latitude, longitude, depth, magnitude, and magnitude type. Only events with magnitude greater than 5.5 were considered, as smaller events are less relevant to disaster preparedness and contribute noise to the predictive models.

4.2 Data Preprocessing

Several preprocessing steps were applied to ensure data quality:

- **Cleaning:** Duplicate and irrelevant entries were removed, and missing values were handled.
- **Normalization:** Continuous variables such as latitude, longitude, depth, and magnitude were normalized to reduce skewness and improve model convergence.
- **Outlier Detection:** The Interquartile Range (IQR) method and the 3-sigma rule were applied to identify and remove extreme outliers in depth and magnitude values.
- **Encoding:** Categorical variables such as magnitude type were numerically encoded where relevant.

4.3 Feature Engineering

The most informative features were selected to maximize predictive power. Latitude, longitude, depth, and magnitude type were identified as the primary predictors of earthquake behaviour. Feature correlations were analysed using heatmaps to eliminate redundancy and multicollinearity.

4.4 Model Training

Four machine learning models were implemented for prediction: Linear Regression, Polynomial Regression, Random Forest Regressor and (LSTM). The dataset was split into training (80%) and testing (20%) subsets. Hyperparameters for Random Forest and LSTM were tuned experimentally to optimize performance.

4.5 Model Evaluation

The models were evaluated using standard statistical metrics:

- **Coefficient of Determination (R^2):** Measures the proportion of variance explained by the model.
- **Mean Squared Error (MSE):** Quantifies the average squared difference between predicted and actual values.
- **Explained Variance:** Assesses the extent to which variability in the data is captured by the model. In addition, visualizations such as scatter plots and residual plots were employed to compare actual versus predicted values, providing further insights into model accuracy and limitations can be seen in Figure 2.

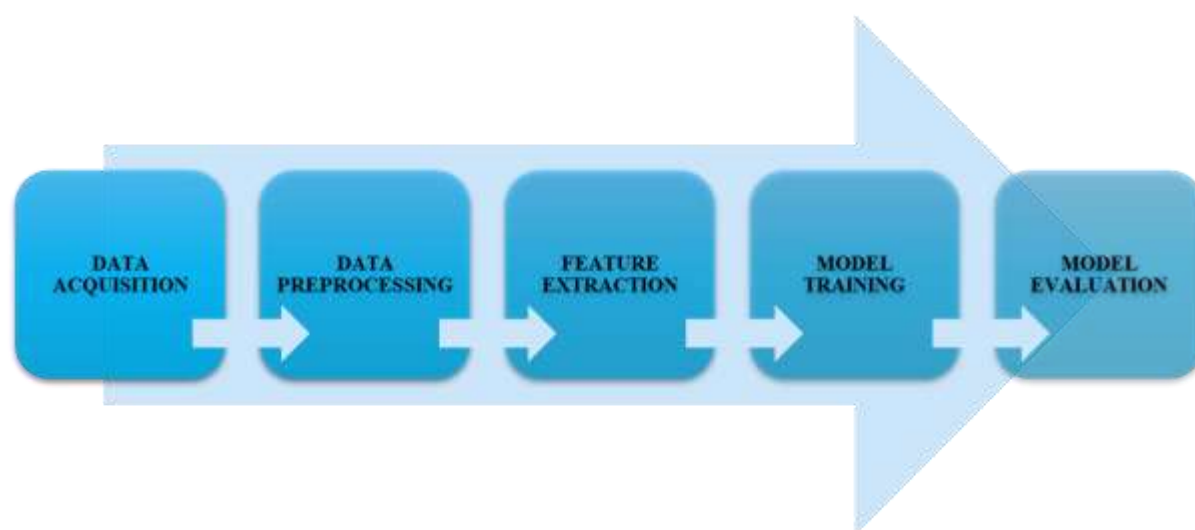


Fig. 2: Methodology workflow for earthquake prediction.

5. EXPERIMENTS AND RESULTS

This section presents the experimental setup, evaluation metrics, and results obtained from the machine learning models implemented for earthquake prediction. The goal is to assess the comparative performance of different algorithms in predicting two key seismic parameters: magnitude and depth.

5.1 Experimental Setup

The dataset was divided into training (80%) and testing (20%) subsets. All models were implemented in Python using the scikit-learn and TensorFlow/Keras libraries. Experiments were conducted on a system with an Intel Core i7 processor, 8 GB RAM, and Windows operating system. Hyperparameters

for Random Forest (number of trees, maximum depth) and LSTM (hidden units, learning rate, epochs) were tuned using a grid search approach.

5.2 Results for Magnitude Prediction

The performance of the models for predicting earthquake magnitude is summarized in Table 1. Among all models, Polynomial Regression achieved the best performance with an R^2 score of 0.92 and the lowest MSE of 0.0341. This demonstrates its ability to effectively capture non-linear patterns in seismic data. In contrast, LSTM underperformed, highlighting its limitations for non-sequential datasets.

Table 1. Model performance for magnitude prediction.

Model	R^2 Score	MSE	Explained Variance
Linear Regression	0.78	0.102	0.79
Polynomial Regression	0.92	0.0341	0.91
Random Forest Regressor	0.87	0.062	0.86
LSTM	<0.60	High	Poor fit

Figure 3 provides a visualization of the Polynomial Regression results, comparing actual versus predicted magnitudes. The close alignment of points along the diagonal line confirms the high predictive accuracy of the model.

5.3 Results for Depth Prediction

Table 2 presents the performance of models for depth prediction. Random Forest Regressor outperformed other methods, achieving an R^2 score of 0.85 and an MSE of 140.23. This highlights the ensemble model's strength in capturing complex feature interactions that influence earthquake depth.

Table 2. Model performance for depth prediction.

Model	R^2 Score	MSE	Explained Variance
Linear Regression	0.62	310.45	0.61
Polynomial Regression	0.70	228.35	0.69
Random Forest Regressor	0.85	140.23	0.84
LSTM	<0.60	High	Poor fit

The visual comparisons in Figure 3, Figure 4, and Figure 5 provide deeper insights into the predictive performance of the models. In Figure 3, Polynomial Regression demonstrates a close alignment between actual and predicted earthquake magnitudes, with data points distributed tightly around the diagonal line. This indicates the model's ability to effectively capture the non-linear nature of seismic magnitude trends, achieving a high R^2 score and low mean squared error. Similarly, Figure 4 illustrates the predictions of Random Forest for earthquake depth. The scatter plot shows a strong correspondence between predicted and observed values, confirming the ensemble model's robustness in handling complex feature interactions such as latitude, longitude, and magnitude type. The relatively compact clustering of points reflects the model's superior accuracy over regression-based and deep learning alternatives for depth estimation.

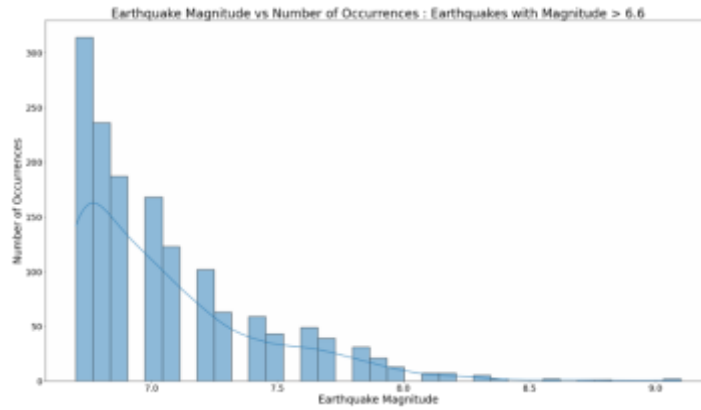


Fig. 3: Actual vs predicted earthquake magnitudes using Polynomial Regression.

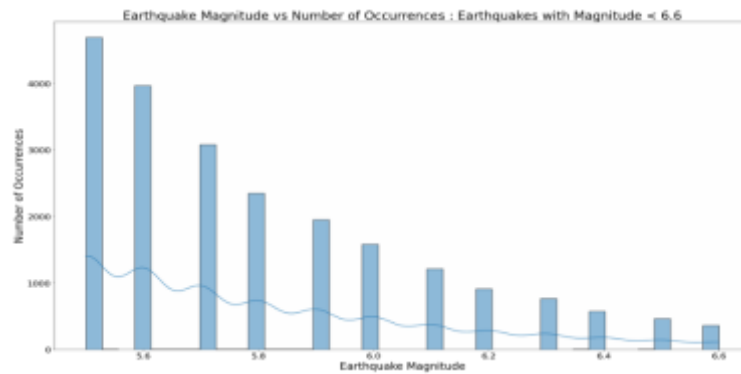


Fig. 4: Actual vs predicted earthquake depths using Random Forest Regressor.

Complementing these results, the heatmap in Figure 5 visualizes feature correlations within the dataset. It reveals that depth and magnitude exhibit weak correlation with geographical coordinates, while non-linear dependencies exist among other seismic attributes.

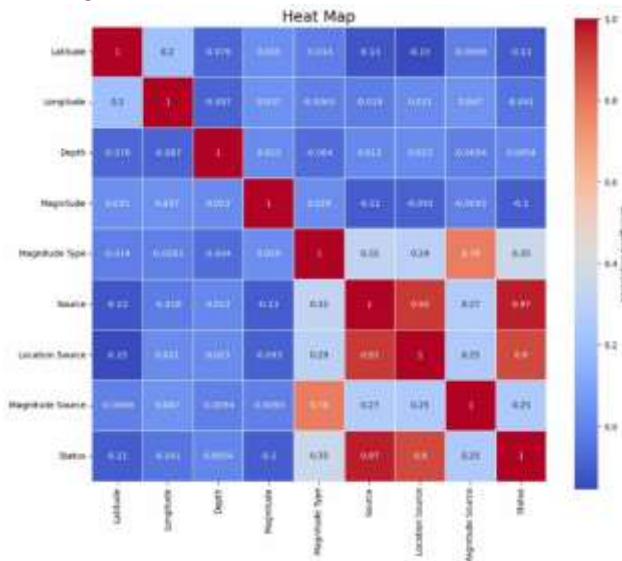


Fig. 5: Point Correlation Analysis (using Heatmap)

This analysis validates the feature selection process and explains why Random Forest and Polynomial Regression outperform models like LSTM, which rely heavily on temporal sequence learning. Together, these figures underscore the importance of selecting algorithms that align with the statistical structure of seismic data, rather than defaulting to deep learning methods.

5.4 Key Findings

The experiments provide three key insights:

1. Polynomial Regression is highly effective for modeling non-linear relationships in magnitude prediction (Table 1, Figure 3).
2. Random Forest Regressor provides the best results for depth prediction, with robust handling of feature interactions (Table 2, Figure 4).
3. LSTM networks underperformed due to the non-sequential structure of the dataset, reaffirming that deep temporal models are unsuitable for static seismic data.

6. DISCUSSION

The experimental results provide important insights into the comparative performance of machine learning models for earthquake prediction. While deep learning approaches such as LSTM are often assumed to outperform classical methods, our findings show that traditional regression and ensemble learning methods remain highly effective when the dataset lacks strong temporal dependencies.

6.1 Polynomial Regression for Magnitude Prediction

Polynomial Regression achieved the best results for magnitude prediction, outperforming both Linear Regression and LSTM. This can be attributed to the non-linear nature of seismic magnitude trends, which cannot be effectively modeled using a simple linear function. The strong R^2 score of 0.92 and low MSE indicate that Polynomial Regression can capture curvilinear patterns in the data. This finding aligns with earlier research by Li and King, who demonstrated that polynomial regression combined with k-nearest neighbours improved aftershock forecasting accuracy. Our results confirm that polynomial-based models remain relevant for seismic datasets where non-linearities dominate.

6.2 Random Forest for Depth Prediction

Random Forest Regressor emerged as the most effective model for depth prediction, with an R^2 score of 0.85. Unlike regression models, Random Forest can handle high-dimensional feature interactions and is less sensitive to noise in the data. These strengths allowed it to outperform both Polynomial Regression and LSTM in predicting depth values. Similar outcomes were reported by Mallouh et al., where Random Forest was found to be superior for classifying seismic events into major and minor categories. This suggests that ensemble methods provide robustness and adaptability for tasks involving multiple correlated features.

6.3 Limitations of LSTM

The underperformance of LSTM highlights an important limitation of deep learning for earthquake prediction. LSTMs are designed for sequential data and excel in capturing temporal dependencies. However, the dataset used in this study, although spanning multiple decades, lacked strong sequential continuity between seismic events. As a result, LSTM struggled to identify meaningful temporal patterns and performed poorly compared to simpler models. This outcome is consistent with findings by Kuyuk

and Susumu, who noted that LSTMs are most effective when applied to real-time seismic streaming data rather than static historical records.

6.4 Implications for Literature and Practice

The results extend the literature in two key ways. First, they reaffirm that ensemble learning methods such as Random Forest remain competitive against deep learning models in domains where feature interactions dominate over temporal dependencies. Second, they highlight the utility of Polynomial Regression as a lightweight yet powerful alternative for non-linear pattern recognition in seismic data. These findings contribute to bridging the gap between traditional statistical modeling and modern deep learning approaches, showing that model choice should be driven by dataset structure rather than trends in algorithm popularity.

From a practical perspective, these insights can inform the development of earthquake early warning systems and risk assessment frameworks. By integrating Polynomial Regression and Random Forest into operational pipelines, authorities could obtain fast and reliable predictions of earthquake parameters, enabling proactive disaster preparedness. Furthermore, the methodology demonstrated here can be scaled to other geospatial prediction tasks such as landslides or flood risk modeling.

7. CONCLUSION AND FUTURE WORK

This research explored the use of multiple machine learning algorithms for earthquake prediction based on historical seismic data obtained from the United States Geological Survey (USGS). The focus was on forecasting two critical earthquake parameters: magnitude and depth. Four models—Polynomial Regression, Random Forest Regressor, Linear Regression, and (LSTM) networks—were systematically compared to evaluate their predictive performance. The analysis revealed three key outcomes. First, Polynomial Regression produced the most accurate results for magnitude prediction, achieving an R^2 value of 0.92 along with the lowest mean squared error (MSE). This demonstrates its capability to capture the inherent non-linear relationships present in seismic records, which are not well represented by simple linear models. Second, Random Forest Regressor excelled in depth prediction, attaining an R^2 score of 0.85. Its strength lies in effectively modeling complex feature interactions while maintaining robustness against noise. Finally, the LSTM network underperformed, largely because the dataset lacked sequential continuity, indicating that models optimized for temporal data are less effective when applied to static seismic records. The contributions of this work are threefold: (i) it delivers a comprehensive comparison of regression, ensemble, and deep learning methods for earthquake prediction; (ii) it highlights Polynomial Regression as a simple yet powerful tool for magnitude estimation; and (iii) it demonstrates the superiority of Random Forest for depth forecasting. These findings emphasize that the choice of predictive models should be guided by the structure of the dataset rather than an assumption that advanced deep learning architectures always yield the best outcomes.

Future Work

Although the proposed framework provides consistent predictions of seismic parameters, there are several directions for extending this research:

- **Real-time Data Integration:** Incorporating live seismic data streams from monitoring networks to enhance the system's applicability for early warning.
- **GIS-based Visualization:** Embedding predictions into Geographic Information Systems (GIS) for generating dynamic hazard maps and supporting risk-aware decision-making.

- Advanced Hybrid Models: Investigating CNN–LSTM hybrids, graph neural networks, or transformer-based models to better capture spatiotemporal dependencies.
- Practical Deployment: Developing user-friendly dashboards or mobile applications to make predictions accessible to scientists, policymakers, and disaster management agencies.

While the precise forecasting of earthquake occurrence remains unattainable with current scientific approaches, this study illustrates that machine learning can deliver meaningful estimates of magnitude and depth. Such predictions can strengthen disaster preparedness and risk mitigation strategies. With further refinement, the presented framework has the potential to evolve into an operational component of earthquake early warning and monitoring systems.

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