International Journal of Innovative Research in Engineering and Management (IJIREM)
ISSN (Online): 2350-0557, Volume-11, Issue-5, October 2024
https://doi.org/10.55524/ijirem.2024.11.5.10
Article ID IJIR3027, Pages 73-82
www.ijirem.org

Comparative Analysis of Machine Learning Models for Earthquake Prediction: A Case Study of Düzce, Türkiye

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Received: 11 September 2024 Revised: 25 September 2024 Accepted: 9 October 2024

ABSTRACT- This paper explores the application of machine learning models, specifically XGBoost, Stacking Regressor, and Long Short-Term Memory (LSTM), for predicting earthquake magnitudes in Düzce, Turkey. The models were trained and tested on seismic data to predict moment magnitude (Mw). The performance of each model was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). The results indicate that the XGBoost model outperforms the other models with a higher R^2 value and lower error metrics, providing a more accurate prediction of seismic events.

KEYWORDS- Earthquake Prediction, LSTM, Machine Learning, Seismic Data, Stacking Regressor, XGBoost.

I. INTRODUCTION

Earthquakes rank among the most catastrophic natural disasters, characterized by sudden occurrences that often leave little time for precautionary measures. The ability to accurately predict seismic events, particularly their magnitude, is crucial for minimizing casualties and infrastructure damage. Traditional methods of earthquake prediction have relied on observable phenomena such as radon emissions from wells, changes in seismic wave velocity, or electromagnetic precursors [1] [3]. However, these approaches have often been limited by high false alarm rates and an inability to fully account for the complexity and non-linearity of seismic data [4], [5].

Over the past decade, machine learning (ML) has emerged as a promising alternative to these traditional techniques. ML-based methods, which include algorithms such as gradient boosting, deep learning, and neural networks, excel at identifying patterns within large datasets that might otherwise be overlooked by conventional models [6] [8]. For instance, ML techniques have been applied successfully in earthquake prediction by utilizing time-series data to model the relationships between different seismic indicators [9], [10]. Among the more recent ML models, XGBoost and Long Short-Term Memory (LSTM) networks have gained attention due to their ability to handle both structured and sequential data, making them ideal for predicting complex natural phenomena like earthquakes [6], [11].

Effective earthquake prediction must account for a wide range of variables, including magnitude, location, and time of occurrence. Past research has shown that these variables are highly stochastic and interdependent, requiring advanced computational techniques to predict them with accuracy [12]. As a result, machine learning models such as XGBoost, which employ gradient boosting to progressively refine its predictions, and LSTM, designed to capture extended dependencies in time-series data, have become increasingly favored in seismic research [13] [14]. These models can also be combined in ensemble learning methods like the Stacking Regressor, which integrates multiple base learners to enhance prediction accuracy [15] [16].

Despite significant advancements, earthquake prediction remains a challenge due to the inherent uncertainty and complexity of seismic events. Many studies continue to focus on improving the accuracy and reliability of prediction models, recognizing that even small improvements can have a substantial impact on disaster preparedness [7] [17]. This study aims to advance these efforts by evaluating the performance of three machine learning models—XGBoost, Stacking Regressor, and LSTM—in forecasting earthquake magnitudes in Düzce, Turkey, a region with a history of significant seismic activity [18]. By evaluating these models, we aim to identify the most effective approach for real-time earthquake prediction and provide insights that could enhance early warning systems and mitigate future disasters [8] [19].

II. RELATED WORK

Machine learning (ML) and deep learning (DL) have been widely adopted across various domains, including health and energy. These advanced computational techniques leverage large datasets and sophisticated algorithms to uncover patterns, make predictions, and enhance decision-making processes. In health, ML algorithms assist in disease diagnosis and treatment planning, while in energy, they are employed for optimizing resource management and predicting demand fluctuations [20] [21].

Recent breakthroughs in machine learning (ML) and deep learning (DL) have revolutionized earthquake forecasting, providing a deeper understanding and more accurate predictions of when, where, and how strong seismic events might occur. Various studies have demonstrated promising improvements in prediction accuracy through the application of sophisticated algorithms and large datasets, identifying patterns in seismic activity that traditional models often struggle to detect.

Various ML techniques were explored for predicting large earthquakes in the North Zagros region, a highly active seismic zone, in [22]. In their study, three ML methods—Artificial Neural Networks (ANN), Random Forest (RF), and Support Vector Machines (SVM)—were applied using nine seismic parameters. The ANN model showed superior performance in forecasting larger magnitude earthquakes. The research highlights the importance of utilizing detailed seismic datasets alongside statistical measures, including recall, accuracy, and precision. By incorporating these metrics, along with the F1-score, prediction accuracy is enhanced, offering promising advancements for managing crises in regions susceptible to earthquakes.

Study [23] implemented advanced deep learning methodologies, featuring Long Short-Term Memory (LSTM), Bi-directional Long Short-Term Memory (Bi-LSTM), and transformer models, to predict earthquake magnitudes across diverse regions, including Japan, Indonesia, and the Hindu-Kush Karakoram (HKKH) area. The evaluation of the models was conducted using metrics such as Mean Absolute Error (MAE) and Mean Squared Error (MSE), revealing that the LSTM model achieved the highest performance for the dataset from Japan. This research shows that deep learning models, especially those that utilize self-attention mechanisms such as transformers, offer strong predictive abilities for earthquake magnitudes between 3.5 M and 6.0 M, highlighting the adaptability of these approaches across various seismic regions.

The effectiveness of recurrent neural networks (RNNs) for earthquake prediction was explored in the study conducted by [18], which concentrated on forecasting seismic events specifically in the Düzce Province of Turkey. This study highlighted the significance of additional geological factors, such as the **b** and **d** values of earthquakes and the distance between the Moon and Earth, in improving prediction accuracy. By employing RNNs for time-series data analysis, the research illustrated the potential for enhanced classification of seismic data and improved forecasting precision.

Furthermore, [24] applied transformer-based models to predict earthquake magnitudes in the Horn of Africa, framing the problem as a multivariate time-series regression task. A comparison of results with LSTM, Bi-LSTM, and Bi-LSTM with attention models revealed that the transformer algorithm outperformed all others, achieving lower errors in metrics such as MAE, MSE, and RMSE. This work underscores the growing relevance of transformer models in seismic prediction due to their capability to process complex time-series data effectively.

Moreover, the research conducted by [25] examined a range of both traditional and modern machine learning algorithms, such as Shallow Neural Networks (SNNs), Support Vector Machines (SVMs), Decision Trees (DTs), and Deep Neural Networks (DNNs), to predict significant upcoming earthquakes in Iran. Their research presented a novel parameter, fault density, which greatly enhanced the predictive accuracy of the models. This finding highlights the critical need to incorporate new seismic parameters into established models to boost their reliability.

Additionally, [26] employed RNNs, LSTM, and Gated Recurrent Units (GRU) to anticipate earthquake-induced dynamic slope reactions, achieving a normalized error of less than ±5%. Their findings illustrate the effectiveness of recurrent models in handling sequential seismic data and improving prediction accuracy when compared to conventional methods. This is consistent with the work of [27], where a CNN model was created to predict earthquakes in northeast India, illustrating that CNNs can make meaningful contributions to earthquake forecasting when adapted to the unique characteristics of specific regions.

There is also a growing interest in hybrid models that combine multiple ML techniques to improve prediction accuracy. Notably, ensemble approaches like the Stacking Regressor have been applied successfully in earthquake prediction tasks [25], offering a method to enhance the robustness of predictions by leveraging the complementary strengths of various models.

Building on recent advancements in earthquake prediction methodologies, this study aims to evaluate the performance of three machine learning models—XGBoost, Stacking Regressor, and LSTM—in predicting earthquake magnitudes within the seismically active region of Düzce, Turkey. These models were selected for their respective strengths in handling complex datasets, forecasting time series, and combining predictions from multiple models. XGBoost was chosen for its robustness in managing non-linear data with high variance, as well as its capacity to offer interpretability through feature importance. LSTM, well-suited for time-series forecasting, aligns with the sequential nature of earthquake occurrences. Stacking Regressor, by integrating the predictions of multiple base models, captures more intricate relationships within the data that may not be fully captured by individual models alone.

Other models, such as Support Vector Machines (SVM) and Artificial Neural Networks (ANN), were initially considered but were ultimately excluded due to their relatively higher computational demands and lower performance in preliminary tests with the Düzce dataset. Although SVM has demonstrated effectiveness in classification tasks, its performance tends to diminish in large-scale regression problems involving highly variable seismic data. By comparing these models, this research contributes to the growing body of literature on machine learning-based seismic forecasting, with the goal of identifying the most reliable approach for real-time earthquake magnitude prediction.

III. METHODOLOGY

A. Data Collection

The seismic dataset utilized in this study encompasses a comprehensive collection of historical earthquake data specifically for the Düzce region of Turkey, covering an extensive time span from 1905 to 2024. This dataset is vital for understanding the seismic activity and potential risks associated with earthquakes in this area, which is known for its tectonic significance due to the presence of major fault lines. The data was sourced from the Boğaziçi University Kandilli Observatory and Earthquake Research Institute Regional Earthquake-Tsunami Monitoring and Evaluation Center, and it can be accessed through the following link: http://www.koeri.boun.edu.tr/sismo/2/earthquake-catalog/.

The dataset comprises several key attributes essential for analyzing seismic events. These attributes include the date of the earthquake formatted as Year/Month/Day, the time of occurrence specified in Coordinated Universal Time (UTC+3), and geospatial coordinates denoting the latitude and longitude for each seismic event. Additionally, it records the depth of the earthquake in kilometers, alongside multiple magnitude readings: MD (Magnitude Derived), ML (Local Magnitude), Mw (Moment Magnitude), Ms (Surface Wave Magnitude), and Mb (Body Wave Magnitude). Each entry in the dataset is uniquely identified by an ID, facilitating precise tracking and analysis of seismic events.

In seismology, various magnitude scales are used to measure the size of an earthquake. The Moment Magnitude (Mw) scale is the most commonly used today, as it provides a more accurate measure of earthquake energy release compared to older scales like the Richter or Local Magnitude (ML) scales. Mw is particularly effective for large quakes, as it accounts for fault slippage and rupture length. Other magnitudes, such as MD (Duration Magnitude) and MS (Surface-wave Magnitude), are also used in specific cases depending on the depth and location of the earthquake. Understanding these magnitude scales is crucial for accurately predicting and analyzing seismic events.

The inclusion of multiple magnitude scales allows for a more nuanced understanding of the earthquakes, as different scales may yield varying estimates of the earthquake's size depending on the distance from the seismic station and the geological conditions. This multifaceted approach enriches the dataset, enabling a thorough exploration of the relationships between different magnitude measures and their implications for seismic risk assessment.

Prior to analysis, the dataset underwent a rigorous preprocessing phase. This step was crucial to ensure data uniformity and reliability, as it involved cleaning the data to eliminate any anomalies or noise that could skew the results. The preprocessing steps included standardization of units, handling missing values, and normalization of data where necessary. By establishing a clean and consistent dataset, the study aimed to enhance the predictive accuracy of the machine learning models employed in the analysis.

In summary, this meticulously curated dataset serves as the foundation for the predictive modeling of earthquake magnitudes in the Düzce region, leveraging both historical insights and robust preprocessing techniques to inform and enhance the machine learning methodologies applied in this research.

B. Machine Learning Models

The study employs three distinct machine learning models to predict earthquake magnitudes, each selected for its unique strengths in handling the complexities of seismic data.

XGBoost: XGBoost is an ensemble-based gradient boosting algorithm that has gained significant recognition for its remarkable accuracy and efficiency, particularly when processing large and complex datasets. This model operates by iteratively enhancing the performance of weak learners, which allows it to effectively identify intricate patterns within seismic data. Its ability to minimize errors through continuous refinement makes XGBoost particularly suitable for predicting earthquake magnitudes, where the underlying relationships can be complex and non-linear.

- ***Stacking Regressor:*** The Stacking Regressor is a sophisticated meta-learning technique that combines predictions from multiple base models, in this case various regression algorithms, to produce a consolidated final prediction. This method capitalizes on the strengths of individual models, allowing for improved predictive performance. By integrating the outputs of diverse algorithms, the Stacking Regressor can capture a wider range of patterns in the data, thereby enhancing the overall robustness and accuracy of the earthquake magnitude predictions.
- ***LSTM (Long Short-Term Memory):*** Long Short-Term Memory networks represent a specialized class of recurrent neural networks (RNNs) tailored for the analysis of time-series data. LSTM architectures are particularly adept at capturing long-term dependencies, making them invaluable for seismic predictions where historical events significantly influence future seismic activity. By maintaining information over extended periods, LSTMs can discern patterns and trends in seismic data that traditional models may overlook, thus providing a more nuanced understanding of earthquake behavior.

XGBoost, a boosting algorithm, creates an ensemble of decision trees to enhance prediction accuracy. By iteratively correcting errors from previous trees, XGBoost delivers highly accurate predictions, making it ideal for handling complex, non-linear relationships in seismic data. LSTM, a type of recurrent neural network (RNN), is specialized for time-series forecasting, allowing the model to remember past information for better future predictions. Lastly, Stacking Regressor combines predictions from multiple models to form a stronger meta-model, thus improving the overall accuracy by leveraging the strengths of each individual model.

Trained on seismic data, these models predict moment magnitudes based on past earthquake events. This approach helps identify patterns that might not be apparent through traditional statistical methods. By using machine learning, we aim to create a more accurate predictive model for earthquake magnitude forecasting.

C. Performance Metrics

The performance of the machine learning models was rigorously evaluated using a set of quantitative metrics designed to provide a comprehensive assessment of prediction accuracy and reliability. The chosen metrics are as follows:

- ***Mean Absolute Error (MAE):*** This metric quantifies the average magnitude of the errors between predicted and actual values, offering a clear and interpretable measure of model performance. By calculating the absolute differences and averaging them, MAE provides insight into the overall accuracy of the predictions, making it a valuable tool for understanding how closely the model's outputs align with observed seismic events.
- ***Root Mean Square Error (RMSE):*** RMSE serves as a robust indicator of prediction accuracy by emphasizing

larger errors. This is accomplished by squaring the residuals (the discrepancies between predicted and actual values), which imposes a greater penalty on larger deviations. This characteristic makes RMSE particularly useful in contexts where large prediction errors are especially detrimental, as it highlights areas where the model may require further refinement.

- ***R^2 (Coefficient of Determination):*** The R^2 value represents the fraction of variance in the from 0 to 1, where higher values suggest a stronger correlation between the model and the actual data. This metric is instrumental in evaluating the effectiveness of the model in capturing the underlying relationships in the data, providing a quantitative measure of the model's explanatory powertarget variable that the model can account for. It spans.

By employing these metrics, the study not only assesses the accuracy of the predictions but also gains insights into the strengths and weaknesses of each model. This multifaceted evaluation approach is crucial for understanding how well each machine learning technique performs in the context of earthquake magnitude prediction, ultimately guiding future improvements in predictive modeling efforts.

IV. RESULTS AND DISCUSSION

The performance of the machine learning models was systematically evaluated based on three key metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2). Table 1 presents a summary of the results obtained for each model. numerals.

Table 1: Performance Metrics of Machine Learning Models for Earthquake Magnitude Prediction

Model	MAE	RMSE	R^2
XGBoost	0.0428	0.3194	0.8400
Stacking Regressor	0.0532	0.4168	0.7276
LSTM	0.1132	0.4393	0.6974

The XGBoost model demonstrated superior performance across all evaluated metrics, achieving the lowest MAE (0.0428) and RMSE (0.3194), alongside the highest R^2 value (0.8400). This indicates that XGBoost provides the most reliable and accurate predictions of earthquake magnitudes within the context of this study. In contrast, the Stacking Regressor exhibited moderate performance, with higher error rates compared to XGBoost. The LSTM model, while useful for capturing temporal dependencies, showed the highest error metrics and the lowest R^2 score (0.6974), positioning it as the least effective model for predicting earthquake magnitudes in this dataset.

While LSTM models are typically powerful for sequential data, the performance in this case was hindered by the relatively limited size of the dataset and the high variance in earthquake magnitudes. LSTM's sensitivity to the length of sequences and the need for large training data makes it more prone to overfitting when fewer data points are available. Additionally, LSTM models may struggle with datasets that have strong temporal dependencies but relatively sparse features, which can lead to increased MAE and RMSE values. In future work, applying techniques such as data augmentation, more advanced regularization methods, or integrating external datasets could potentially improve LSTM's performance.

The models used in this study, particularly XGBoost, have the potential to be integrated into real-time earthquake early warning systems. By continuously analyzing seismic data in real-time, such models could provide early predictions of earthquake magnitudes, allowing for timely warnings and mitigation efforts. This integration would be especially beneficial in seismically active regions like Turkey, where rapid response is critical to minimizing damage. Moreover, the methodologies used in this study could be adapted for other earthquake-prone regions, such as the Pacific Ring of Fire, to enhance global earthquake preparedness and risk management efforts.

A. *Prediction Accuracy*

Table 2 illustrates a comparison of true earthquake magnitudes (Mw) against the predictions made by the three models. This comparison is essential for understanding the practical implications of the model performances.

Table 2: Comparison of True Earthquake Magnitudes and Model Predictions

True Mw	XGBoost Predictions	Stacking Predictions	LSTM Predictions
0	5.2879E-06	3.9708E-06	-0.0110
3.3	3.3979	3.3565	2.8097
7.2	6.3330	2.9929	2.8788

The XGBoost model consistently yielded predictions that were significantly closer to the true Mw values across the board. Notably, for larger magnitude events, such as Mw 7.2, the XGBoost prediction (6.3330) was the most accurate, while the Stacking Regressor and LSTM models considerably underestimated this magnitude. This discrepancy underscores the importance of model selection in the context of seismic prediction, as accurate forecasts are crucial for risk assessment and mitigation strategies in earthquake-prone regions.

B. *Visualizing Prediction Results*

In this section, we present several visualizations that illustrate the performance of the different machine learning models used in our study.

Figure 1 illustrates a correlation matrix the relationships between various features used in the models. This matrix helps identify which seismic parameters are strongly correlated with earthquake magnitudes, potentially guiding future model improvements.

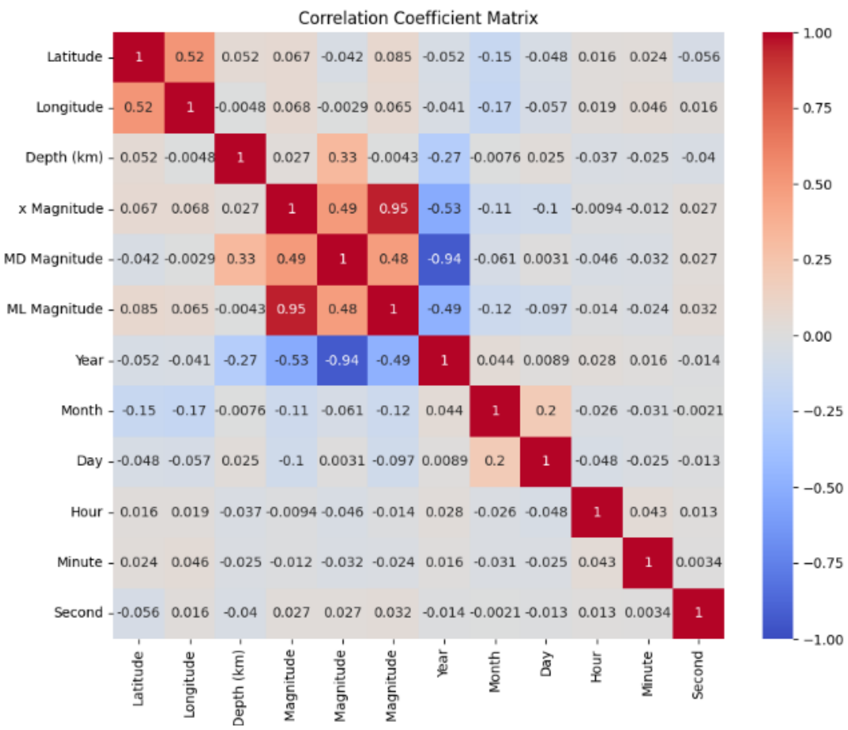

Figure 1: Correlation matrix

Figure 2 illustrates the XGBoost model's predictions, showcasing its performance in predicting earthquake magnitudes. The alignment of predicted and actual values is critical for assessing the model's reliability, as it demonstrates the model's capability in accurately forecasting seismic events.

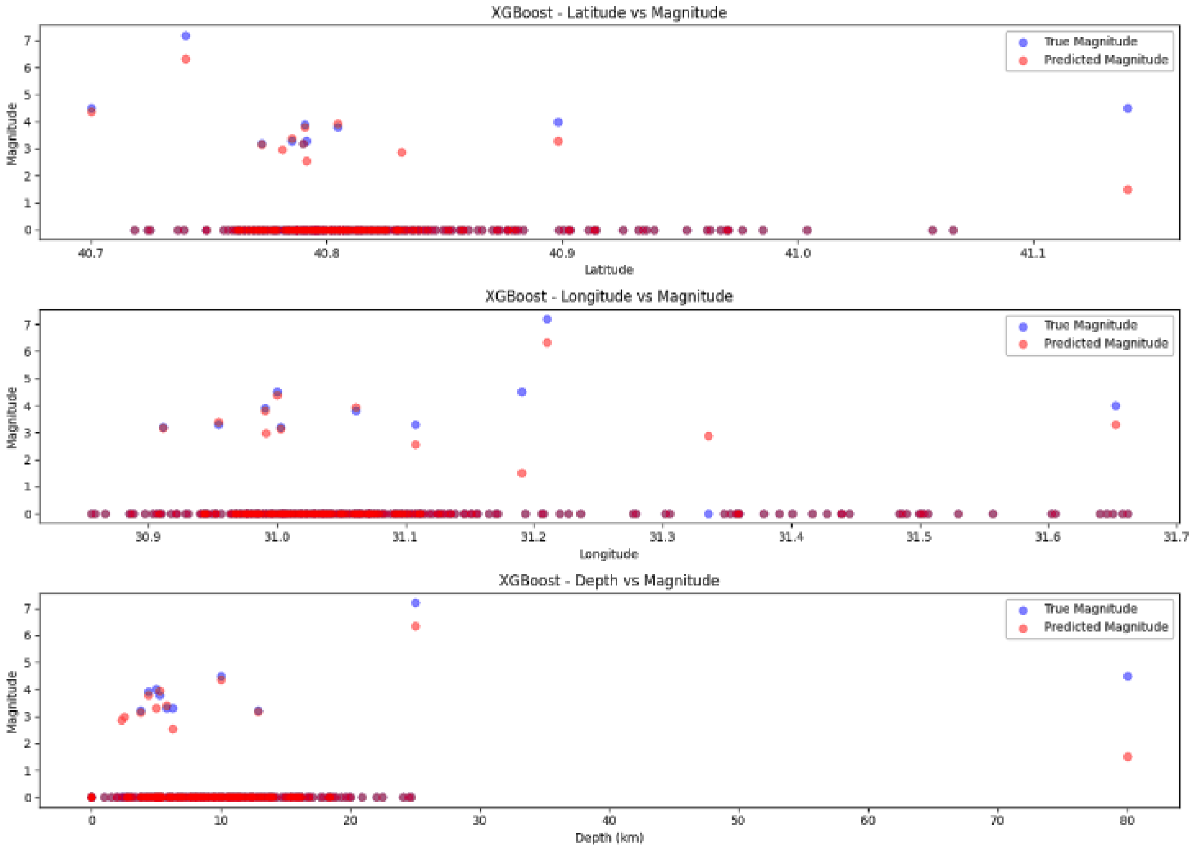

Figure 2: XGBoost vs. Magnitude

Figure 3 presents the predictions made by the stacking regressor model. By comparing these predictions with the actual magnitudes, we can evaluate the stacking regressor's overall prediction capabilities and its effectiveness in handling complex relationships within the seismic data.

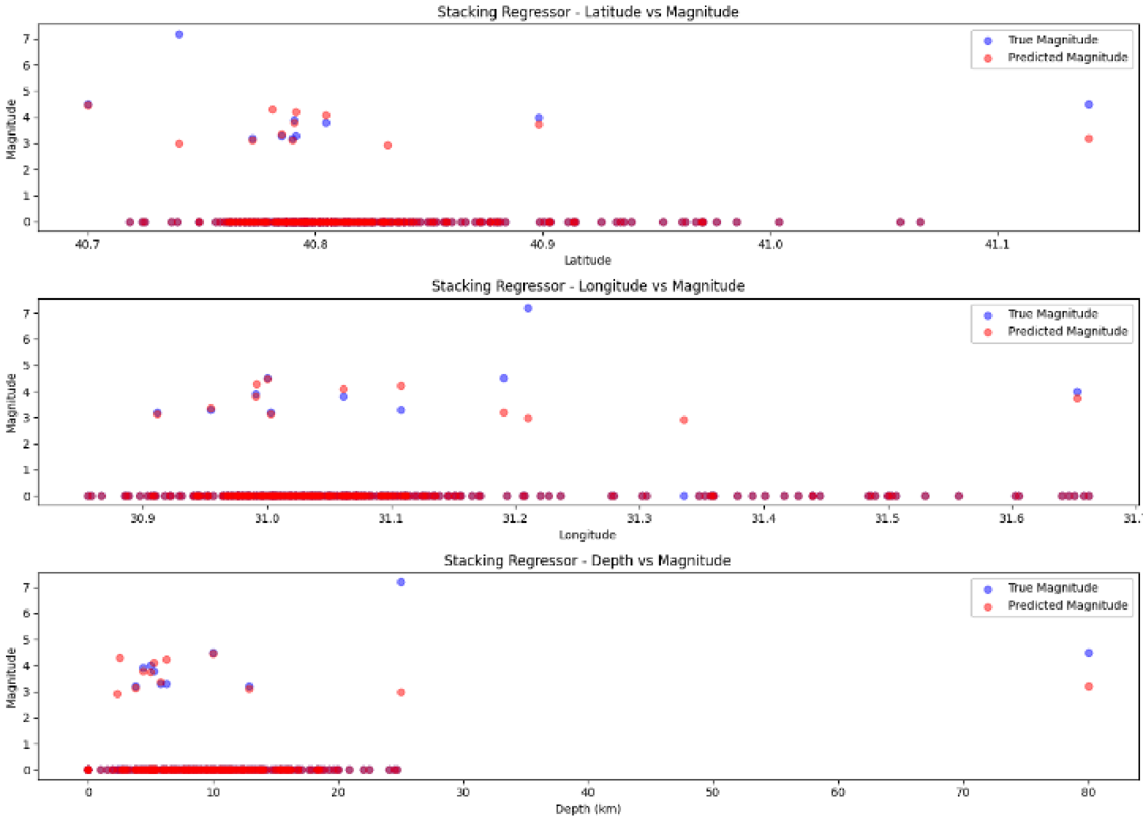

Figure 3: Stacking Regressor vs. Magnitude

Figure 4 compares the predicted magnitudes from the Long Short-Term Memory (LSTM) model against the actual magnitudes. Observing the distribution of predicted values in relation to the actual values provides insights into the LSTM model's effectiveness, highlighting its strengths and potential areas for improvement in earthquake magnitude forecasting.

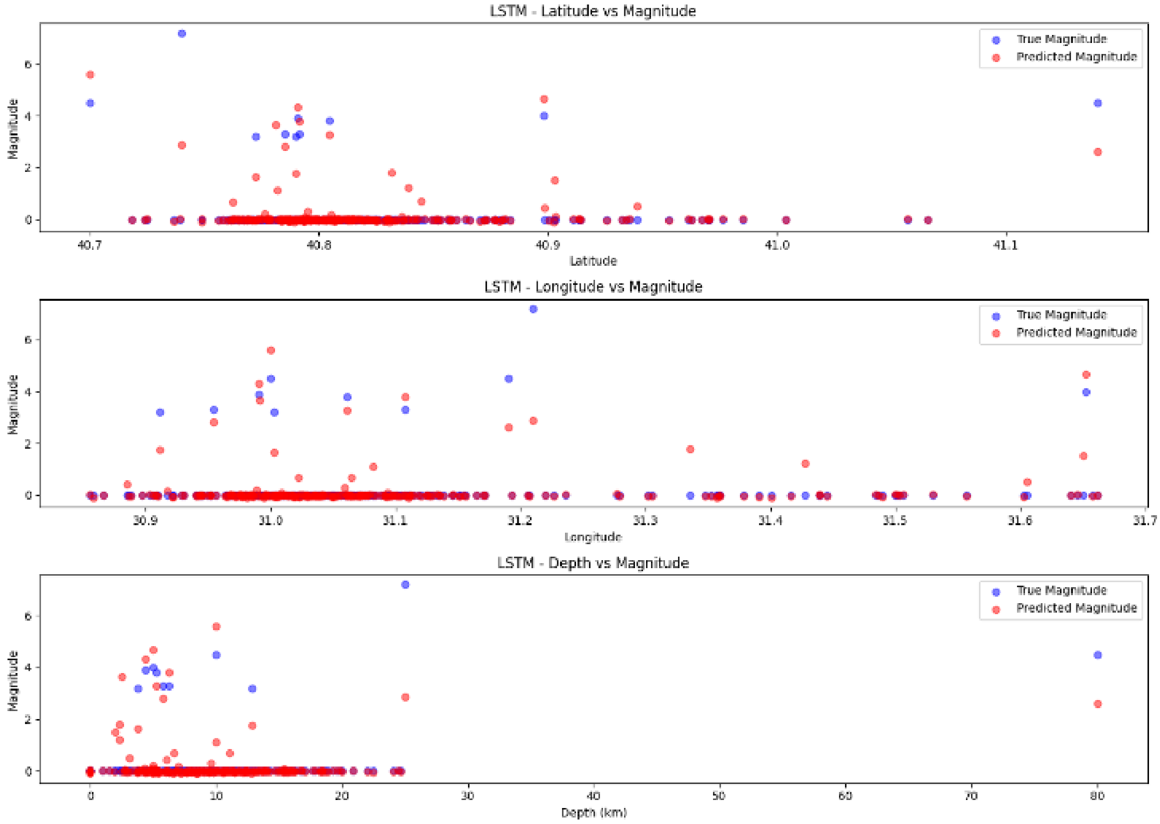

Figure 4: LSTM vs. Magnitude

Figure 5 displays the relationship between the actual earthquake magnitudes and the predicted values generated by our models. This comparison is crucial for assessing the overall performance of the models, as it visually represents how closely the predicted values align with the actual magnitudes, thereby indicating the accuracy and reliability of the forecasting methods employed.

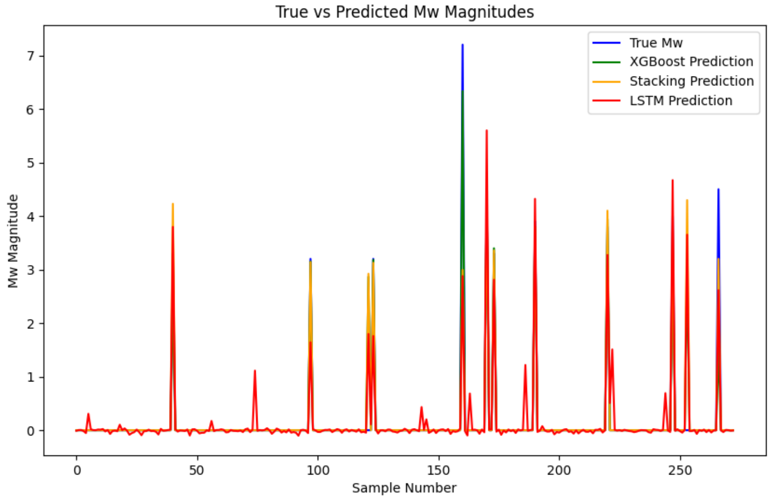

Figure 5: Model predictions comparison

Figure 6 illustrates the accuracy comparison of the XGBoost, Stacking Regressor, and LSTM models, showcasing their respective predictive performances. A higher accuracy percentage indicates greater effectiveness in forecasting earthquake magnitudes, underscoring the strengths of each model. This visual representation facilitates a clear understanding of how well each model performs in capturing the underlying patterns in seismic data, allowing for an informed assessment of which approach may be more suitable for real-time predictions.

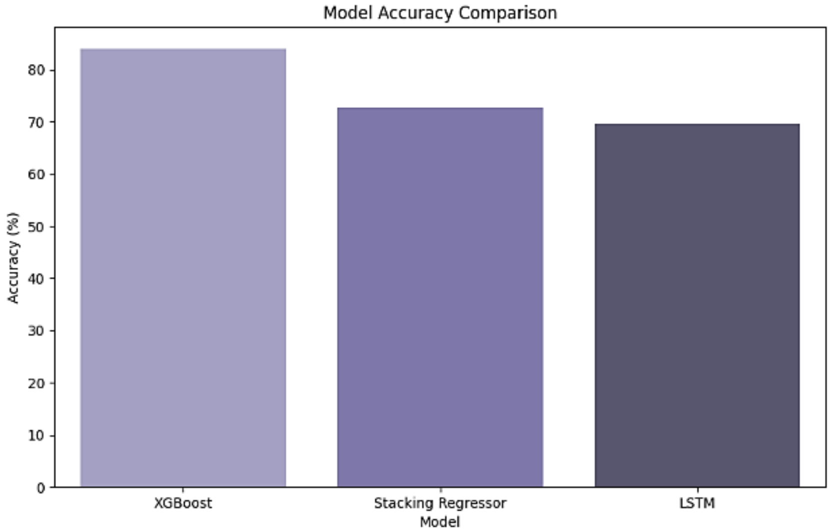

Figure 6: Model accuracy

Figure 7 presents the confusion matrix heatmap, providing a visual representation of the performance of our classification models. This matrix allows us to evaluate how well the model can distinguish between different classes of earthquake magnitudes. Each cell in the matrix represents the number of instances predicted in each category compared to the actual categories, offering insights into the model's classification accuracy and identifying areas where improvements may be needed.

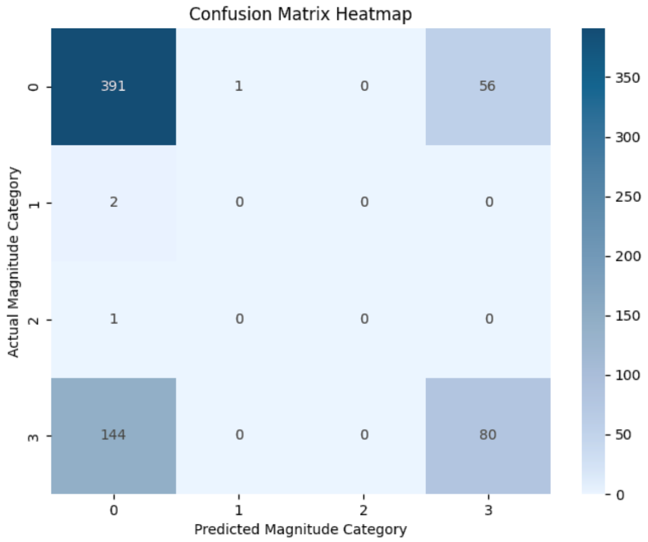

Figure 7: Confusion matrix heatmap

Figure 8 illustrates the feature importance chart, highlighting the significance of each input feature in contributing to the model's predictions. By evaluating the relative importance of various features, we gain insights into which factors are most influential in predicting earthquake magnitudes. This analysis not only helps in understanding the models' decision-making processes but also guides future data collection efforts by identifying key variables that warrant further exploration in seismic forecasting.

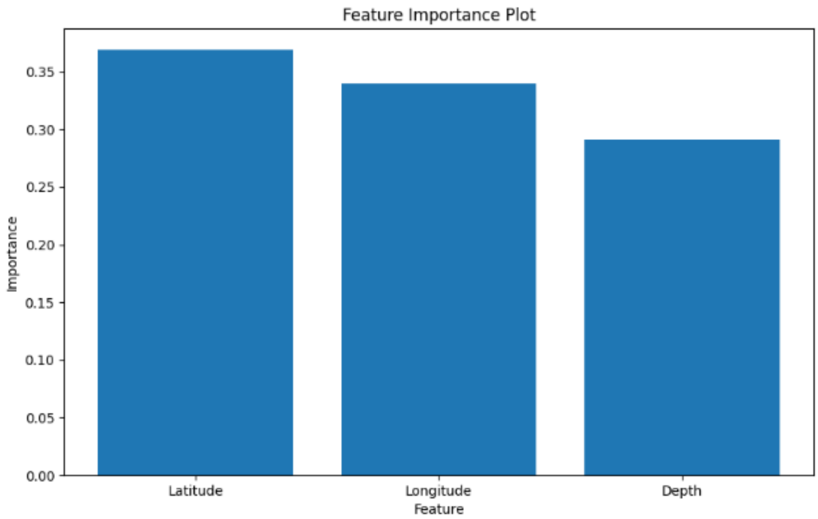

Figure 8: Feature importance

Figure 9 presents the F1 Score chart categorized by earthquake magnitudes, offering an in-depth analysis of the models' effectiveness across various levels of seismic activity. The F1 score, being the harmonic mean of precision and recall, provides a balanced measure of a model's accuracy in classification tasks, particularly when addressing imbalanced datasets. In this analysis, the F1 score is calculated for each category of earthquake magnitudes, allowing us to evaluate how well the models predict events within specific ranges. Elevated F1 scores indicate that the models successfully recognize true positive cases while effectively minimizing the occurrence of false positives and false negatives, thereby enhancing the reliability of predictions in critical seismic scenarios.

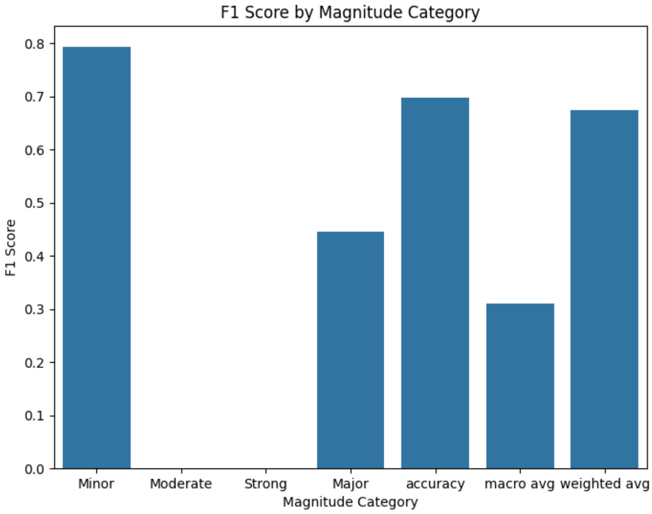

Figure 9: F1 Score by magnitude category

V. CONCLUSION

This study highlights the significant potential of machine learning models, particularly the XGBoost algorithm, in predicting earthquake magnitudes in the Düzce region of Turkey. The results indicate that while all models demonstrated reasonable predictive capabilities, XGBoost exhibited superior performance compared to the Stacking Regressor and LSTM models. Its ability to handle the complex patterns inherent in seismic data underscores its robustness and effectiveness in this application.

Looking ahead, future research will aim to enhance model accuracy by incorporating a broader range of seismic and environmental variables. Extending this study to other earthquake-prone regions will also provide valuable insights and improve generalizability. Furthermore, the integration of these predictive models into real-time prediction and early warning systems holds great promise for mitigating earthquake-related damage and improving public safety.

In conclusion, this study demonstrates the efficacy of machine learning models, particularly XGBoost, in predicting earthquake magnitudes. However, future research should focus on integrating additional features, such as soil composition and aftershock sequences, which could further enhance prediction accuracy. Moreover, applying transfer learning techniques across different tectonic regions could provide a more generalized model for global earthquake prediction. The potential for real-time application in early warning systems highlights the practical significance of this research, with the ultimate goal of reducing the impact of seismic events on vulnerable populations.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

REFERENCES

[1] I. M. Murwantara, P. Yugopuspito, and R. Hermawan, “Comparison of machine learning performance for earthquake prediction in Indonesia using 30 years historical data,” TELKOMNIKA Telecommun. Comput. Electron. Control., vol. 18, no. 3, p. 1331, Jun. 2020, Available From: http://doi.org/10.12928/telkomnika.v18i3.14756

[2] L. Sevgi, “A critical review on electromagnetic precursors and earthquake prediction,” Turkish Journal of Electrical Engineering and Computer Sciences, 2007. Available From: https://journals.tubitak.gov.tr/elektrik/vol15/iss1/1/

[3] J. H. Whitcomb, J. D. Garmany, and D. L. Anderson, “Earthquake Prediction: Variation of Seismic Velocities before the San Francisco Earthquake,” Science, vol. 180, no. 4086, pp. 632–635, May 1973, Available From: https://doi.org/10.1126/science.180.4086.632

[4] M. R. Andi Purnomo, “A Bayesian Reasoning for Earthquake Prediction Based on IoT System,” J. Phys. Conf. Ser., vol. 1471, no. 1, p. 012022, Feb. 2020, Available From: https://doi.org/10.1088/1742-6596/1471/1/012022

[5] A. Riggio and M. Santulin, “Earthquake forecasting: A review of radon as seismic precursor,” Boll. di Geofis. Teor. ed Appl., 2015, Available From: https://ricerca.ogs.it/handle/20.500.14083/1175

[6] M. Mondol, “Analysis and Prediction of Earthquakes using different Machine Learning techniques,” 35th Twente Student Conf. IT, 2021. Available From: https://essay.utwente.nl/87313/

[7] F. Azam, M. Sharif, M. Yasmin, and S. Mohsin, “Artificial Intelligence Based Techniques for Earthquake Prediction: a Review,” Sci. Int. (Lahore), 2014. Available From: https://shorturl.at/U93HB

[8] J. L. Martín Núñez and A. D. Lantada, “Artificial intelligence aided engineering education: State of the art, potentials and challenges,” Int. J. Eng. Educ., 2020. Available From: https://www.ijee.ie/1atestissues/Vol36-6/03_ijee3984.pdf

[9] J. Asefa and A. Ayele, “Seismicity of the East African Rift System for the period 2013 to 2016,” J. African Earth Sci., vol. 183, p. 104315, Nov. 2021, Available From: https://doi.org/10.1016/j.jafrearsci.2021.104315

[10] V. Gitis, A. Derendyaev, and K. Petrov, “Analyzing the Performance of GPS Data for Earthquake Prediction,” Remote Sens., vol. 13, no. 9, p. 1842, May 2021, Available From: https://doi.org/10.3390/rs13091842

[11] M. N. Brykov et al., “Machine Learning Modelling and Feature Engineering in Seismology Experiment,” Sensors, vol. 20, no. 15, p. 4228, Jul. 2020, Available From: https://doi.org/10.3390/s20154228

[12] P. Kavianpour, M. Kavianpour, E. Jahani, and A. Ramezani, “A CNN-BiLSTM model with attention mechanism for earthquake prediction,” J. Supercomput., vol. 79, no. 17, pp.

19194–19226, Nov. 2023, Available From: https://doi.org/10.1007/s11227-023-05369-y

[13] H. Alaskar and T. Saba, "Machine Learning and Deep Learning: A Comparative Review," Springer, 2021, pp. 143–150, Available From: https://doi.org/10.1007/978-981-33-6307-6_15

[14] J. Faouzi and H. Janati, "Pyts: A python package for time series classification," J. Mach. Learn. Res., 2020. Available From: https://www.jmlr.org/papers/v21/19-763.html

[15] L. Krischer et al., "ObsPy: a bridge for seismology into the scientific Python ecosystem," Comput. Sci. Discov., vol. 8, no. 1, p. 014003, May 2015, Available From: https://doi.org/10.1088/1749-4699/8/1/014003

[16] A. Hoque, J. Raj, and A. Saha, "Approaches of Earthquake Magnitude Prediction Using Machine Learning Techniques," SSRN Electron. J., 2018, Available From: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3513365

[17] J. W. Kim, H. Y. Joo, R. Kim, and J. H. Moon, "Investigation of the relationship between earthquakes and indoor radon concentrations at a building in Gyeongju, Korea," Nucl. Eng. Technol., vol. 50, no. 3, pp. 512–518, Apr. 2018, Available From: https://doi.org/10.1016/j.net.2017.12.010

[18] T. Pura, P. Güneş, A. Güneş, and A. A. Hameed, "Earthquake Prediction for the Düzce Province in the Marmara Region Using Artificial Intelligence," Appl. Sci., vol. 13, no. 15, p. 8642, Jul. 2023, Available From: https://doi.org/10.3390/app13158642

[19] A. Skelton et al., "Changes in groundwater chemistry before two consecutive earthquakes in Iceland," Nat. Geosci., vol. 7, no. 10, pp. 752–756, Oct. 2014, Available From: https://www.nature.com/articles/ngeo2250

[20] V. Kushawaha, G. Gupta, and L. Singh, "Enhancing Energy Efficiency: Advances in Smart Grid Optimization," Int. J. Innov. Res. Eng. Manag., vol. 11, no. 2, pp. 100–105, May 2024, Available From: https://doi.org/10.55524/ijirem.2024.11.2.20

[21] S. Dara et al., "Cardiovascular Disease Prediction Using Machine Learning Approaches," Int. J. Innov. Res. Eng. Manag., vol. 10, no. 2, pp. 133–135, Sep. 2023, Available From: https://doi.org/10.55524/ijirem.2023.10.2.27

[22] S. Ommi and M. Hashemi, "Machine learning technique in the north zagros earthquake prediction," Appl. Comput. Geosci., vol. 22, p. 100163, Jun. 2024, Available From: https://doi.org/10.1016/j.acags.2024.100163

[23] B. Sadhukhan, S. Chakraborty, and S. Mukherjee, "Predicting the magnitude of an impending earthquake using deep learning techniques," Earth Sci. Informatics, vol. 16, no. 1, pp. 803–823, Mar. 2023, Available From: https://doi.org/10.1007/s12145-022-00916-2

[24] E. Abebe, H. Kebede, M. Kevin, and Z. Demissie, "Earthquakes magnitude prediction using deep learning for the Horn of Africa," Soil Dyn. Earthq. Eng., vol. 170, p. 107913, Jul. 2023, Available From: https://doi.org/10.1016/j.soildyn.2023.107913

[25] M. Yousefzadeh, S. A. Hosseini, and M. Farnaghi, "Spatiotemporally explicit earthquake prediction using deep neural network," Soil Dyn. Earthq. Eng., vol. 144, p. 106663, May 2021, Available From: https://doi.org/10.1016/j.soildyn.2021.106663

[26] Y. Huang, X. Han, and L. Zhao, "Recurrent neural networks for complicated seismic dynamic response prediction of a slope system," Eng. Geol., vol. 289, p. 106198, Aug. 2021, Available From: https://doi.org/10.1016/j.enggeo.2021.106198

[27] R. Jena, B. Pradhan, S. P. Naik, and A. M. Alamri, "Earthquake risk assessment in NE India using deep learning and geospatial analysis," Geosci. Front., vol. 12, no. 3, p. 101110, May 2021, Available From: https://doi.org/10.1016/j.gsf.2020.11.007