Uluslararası İleri Doğa Bilimleri ve Mühendislik Araştırmaları Dergisi
Sayı 9, S. 226-237, 3, 2025

Araştırma Makalesi

International Journal of Advanced Natural Sciences and Engineering Researches
Volume 9, pp. 226-237, 3, 2025

Research Article

https://as-proceeding.com/index.php/ijanser
ISSN:2980-0811

Vibration of Time: Earthquake Magnitude Prediction Using Machine Learning and Graphical Representation of Earthquakes from 1900 to 2023

Eyyüp Yalçın*, Sinem Akyol [2]

[1]Software Engineering/Research Institute, Fırat University, Turkey
[2] Software Engineering/Research Institute, Fırat University, Turkey

*(eyyupyalciin@gmail.com) Email of the corresponding author

(Received: 06 March 2025, Accepted: 07 March 2025)

(4th International Conference on Recent Academic Studies ICRAS 2025, March 04-05, 2025)

ATIF/REFERENCE: Yalçın, E. & Akyol, S. (2025). Vibration of Time: Earthquake Magnitude Prediction Using Machine Learning and Graphical Representation of Earthquakes from 1900 to 2023. *International Journal of Advanced Natural Sciences and Engineering Researches*, 9(3), 226-237.

Abstract – An earthquake is a natural disaster that significantly impacts human life and structures. This study aims to contribute to the understanding of this important issue through a comprehensive evaluation of earthquakes from geological, seismological, and engineering perspectives. Hypotheses developed by assessing the effects of plate tectonics, volcanic activities, and anthropogenic triggers on earthquakes analyze the formation process and risk profiles of earthquakes. The strategic importance of determining the risk profiles of geographical regions in terms of earthquake potential has been emphasized, with a focus on earthquake zones and hazard analyses.

The dataset, consisting of earthquakes from 1900 onwards, was used as a sample, and various machine learning models were applied to this data. Models used include Random Forest, Gradient Boosting, XGBoost, Linear Regression, Ridge Regression, Lasso Regression, and Support Vector Regression. The performance of these models in predicting earthquake magnitude was compared, and it was found that the XGBoost model showed the best performance with the lowest Mean Squared Error (MSE).

The results demonstrate that machine learning models have significant potential in predicting earthquake magnitudes. This study aims to evaluate community preparedness for earthquakes by addressing the role of exploratory data analysis with artificial intelligence in earthquake risk analysis and prediction. By providing a multifaceted analysis of earthquakes, this study makes an important contribution to the academic literature.

Keywords – Earthquake Prediction, Machine Learning, Risk Analysis, Artificial Intelligence.

I. INTRODUCTION

Earthquakes are natural disasters that occur as a result of dynamic processes within the Earth's crust, reflecting the constantly changing and evolving nature of the planet's surface. They are characterized by vibrations caused by the sudden release of energy from rocks in the Earth's crust and typically lead to varying effects depending on factors such as magnitude, depth, and local geological conditions. This article focuses on earthquake magnitude prediction and the multidimensional analysis of earthquakes, providing a comprehensive examination of the impacts, causes, and types of magnitudes associated with these natural disasters.

Among the different scale systems used to measure earthquake magnitude are the Richter scale, Moment Magnitude scale (Mw), and Surface Wave Magnitude (Ms). This article will provide a detailed explanation of the fundamental principles and advantages of each scale system, while thoroughly exploring the complexities of earthquake magnitude measurement and how these scales can be used to assess the potential danger of an earthquake.

In conclusion, this article aims to make a significant contribution to understanding the multifaceted nature of earthquakes and preparing societies for future similar events. The detailed analyses presented in this study will allow us to better understand the impacts of earthquakes and develop more effective disaster management strategies.

In this article, we focus on analyzing earthquake data in detail and developing prediction models using machine learning techniques. The dataset forming the foundation of our analysis includes various characteristics of earthquake events, such as magnitude, depth, location, and historical data. To understand this dataset and identify important patterns related to earthquakes, we have applied Exploratory Data Analysis (EDA) methods and various machine learning models.

EDA (Exploratory Data Analysis) is a powerful tool used to understand the basic features of a dataset, visualize distributions, examine relationships between variables, and uncover potential patterns within the data. In this article, the analysis of earthquake data using various techniques and the evaluation of this data with machine learning models will be emphasized. The goal is to reveal important insights related to earthquakes and explore how this information can contribute to future earthquake management and risk reduction strategies.

Further, the article will focus on the detailed results of predictions made using machine learning models, along with the application of EDA to the earthquake data. The models employed include Random Forest, Gradient Boosting, XGBoost, Linear Regression, Ridge Regression, Lasso Regression, and Support Vector Regression. A comparison of the performance of these models will highlight the superior performance of the XGBoost model. This analysis will enable us to better understand the characteristics of earthquake events and assess earthquake risks more effectively. It is expected that these insights will make a significant contribution to disaster management and the preparedness of societies for earthquakes.

II. EARTHQUAKE

Earthquakes are natural disasters that can cause significant damage and loss of life. Predicting earthquakes is a complex and challenging task due to the intricate structure of the Earth's crust and the unpredictability of seismic events [1].

Additionally, real-time seismology and earthquake early warning systems have been proposed as effective tools to mitigate earthquake damage by providing timely alerts, enabling necessary precautions to be taken [2]. These systems utilize data from sources such as GPS and geoelectric field signals to estimate earthquake magnitude and assess associated risks [3].

Risk assessment also plays a critical role in understanding the potential impact of earthquakes on vulnerable regions. Studies have evaluated earthquake risk using geospatial analysis and GIS-based approaches, considering factors such as population density, slope displacement, and seismic hazards [4]. Moreover, the development of risk assessment systems like the Major Earthquake Risk Assessment System has provided valuable tools for evaluating earthquake risks in specific geographical regions [5].

Despite these advancements, the unpredictability of earthquakes remains a significant challenge. Some researchers have emphasized the difficulty of accurately predicting earthquakes due to the complexity of seismic systems and the lack of consistent prediction parameters [6]. Furthermore, the evaluation of earthquake prediction capabilities has been regarded as a challenging and slow process, highlighting the ongoing complexities in this field [7].

In conclusion, while significant progress has been made in earthquake prediction and risk assessment, the complexity and unpredictability of seismic events continue to present ongoing challenges. Continued research and technological advancements are essential to enhance our understanding of earthquakes and improve our ability to predict their impacts.

III. EXPLORATORY DATA ANALYSIS

To understand seismic activity and assess its consequences, various studies have been conducted to explore different aspects of earthquakes [2]. Allen and Ziv (2011) examined the application of real-time GPS in earthquake early warning systems, emphasizing the potential of GPS data to complement existing seismic methodologies. Additionally, Chartier et al. (2017) provided insights into earthquake rupture velocity prediction, highlighting the importance of understanding magnitude-frequency distribution of fault segments and specific slip rates [8]. Furthermore, Bao et al. (2019) delved into the supershear rupture of the 2018 Palu earthquake, verifying its continuous supershear velocity through regional seismograms [9].

Li et al. (2022) emphasized the importance of scientific decision-making and rescue efforts in mitigating the immediate consequences of earthquake disasters, focusing specifically on earthquake-related fatalities in mainland China [10]. Xiong et al. (2010) examined longwave radiation anomalies associated with earthquakes, demonstrating intense radiation concentrations in epicentral regions before earthquakes [11]. Moreover, Nettles & Ekström (1998) shed light on fault mechanisms by linking anomalous earthquakes near the Bárdarbunga Volcano to the inflation of a shallow magma chamber and stress loading on a deep ring fault.

In the context of specific earthquake events, Fang et al. (2019) analyzed the Mw 7.5 Palu earthquake, highlighting its occurrence in a triple junction region involving converging tectonic plates [12]. Sharma et al. (2017) introduced the Earthquake Damage Visualization (EDV) technique for rapid detection of earthquake-induced damage using Synthetic Aperture Radar (SAR) data, providing an advanced approach to assess earthquake impacts [13]. Additionally, Guo et al. (2022) investigated the impact zone of the 2017 Jiuzhaigou earthquake, revealing a significant decline in mobile signals after the earthquake [14].

These studies contribute to a comprehensive understanding of earthquakes, encompassing topics such as early warning systems, rupture velocity prediction, specific earthquake events, and the assessment of earthquake impacts. By integrating these findings, researchers and policymakers can enhance preparedness, response, and mitigation strategies against seismic events.

A. Types of EDA

Exploratory Data Analysis (EDA) refers to statistical and graphical techniques used to understand the features, patterns, and relationships within a dataset. There are several main types of EDA:

- Univariate Analysis

This type of analysis examines the statistical properties and distribution of a single variable (column). Graphical representations such as histograms, box plots, and density plots are frequently used. Measures of central tendency (e.g., mean, median), measures of spread (e.g., standard deviation), and basic statistical properties are part of this analysis.

- Bivariate Analysis

This type is used to understand the relationship between two variables. Techniques such as scatter plots, correlation analysis, and regression analysis are commonly employed. The strength and linearity of the relationship between two variables are the primary focus of this analysis.

- Multivariate Analysis

This analysis involves examining multiple variables simultaneously. It aims to understand patterns and discover complex relationships within multidimensional datasets. Techniques such as multiple regression analysis, factor analysis, and cluster analysis are examples of this type of analysis.

- Time Series Analysis

This analysis is used for studying variables that change over time. It is applied to understand trends, seasonal effects, and cycles. Time series plots, autocorrelation analysis, and spectral analysis are commonly used methods in this type of analysis.

- Geographical Analysis

Geographical analysis is employed to understand patterns and relationships in spatial datasets. Tools such as maps, Geographic Information Systems (GIS), and spatial statistics are part of this analysis. For earthquake analysis, examining the geographical distribution of earthquakes is an example of this type.

IV. MATERIALS AND METHOD

This research utilized a comprehensive dataset containing information on earthquakes that have occurred worldwide since 1900. The dataset, obtained from the United States Geological Survey (USGS), is updated weekly. The objective of the study is to analyze trends, geographical distributions, and evolving characteristics of earthquakes over time, contributing to earthquake risk management and disaster response strategies.

For analytical purposes, earthquake data were evaluated using statistical and graphical tools. Factors such as earthquake frequency, magnitude, geographical distribution, and temporal changes were examined, providing a broad perspective on seismic activities. Machine learning models were also employed to predict earthquake magnitudes.

A. *Dataset*

As the primary material, the dataset from the reliable USGS earthquake catalog formed the foundation of the study. The meaning of each column in the dataset—such as time, latitude, longitude, depth, and magnitude—was explained in detail. The sources from which this information was collected and the processes used to handle this data were also specified comprehensively. It is shown in Table 1.

Table 1. Features of the Dataset and Descriptions

Feature Name	Description
time	The time of the earthquake, reported as the number of milliseconds since the Unix epoch (January 1, 1970, 00:00:00 UTC).
latitude	The latitude of the earthquake's epicenter, reported in decimal degrees.
longitude	The longitude of the earthquake's epicenter, reported in decimal degrees.
depth	The depth of the earthquake, reported in kilometers.
mag	The magnitude of the earthquake, reported in various magnitude scales (see magType column).
magType	The type of magnitude used to report the earthquake magnitude (e.g., "mb," "ml," "mw").
nst	The total number of seismic stations used to calculate the earthquake's location and magnitude.
gap	The largest azimuthal gap between adjacent stations, in degrees.
dmin	The minimum distance to the nearest station, in degrees.
rms	The root mean square of residuals relative to the earthquake's location.
net	The network identifier for the seismic network used to locate the earthquake.
id	The unique identifier for the earthquake event.
updated	The most recent update time of the earthquake event in the catalog, reported in milliseconds since the Unix epoch.
place	A human-readable description of the earthquake's location.
type	The type of seismic event (e.g., "earthquake," "quarry blast," "explosion").
horizontalError	The horizontal error of the location reported in the latitude and longitude columns, in kilometers.
depthError	The error in the depth column, reported in kilometers.
magError	The estimated standard error of the reported earthquake magnitude.
magNst	The number of seismic stations used to calculate the earthquake's magnitude.
status	The status of the earthquake event in the USGS earthquake catalog (e.g., "reviewed," "automatic").
locationSource	The identifier of the organization or network providing the earthquake location.
magSource	The identifier of the organization or network providing the earthquake magnitude.

Statistical Analysis of Numerical Variables

The table presents the fundamental statistics of the earthquake dataset. Each statistic reveals characteristics of a specific numerical variable within the dataset. It is shown in Table 2.

Table 2. Statistical Analysis of Numerical Variables

	count	mean	std	min	25%	50%	75%	max
Unnamed :0	99749.000000	49874.000000	28795.200338	0.000000	24937.000000	49874.000000	74811.000000	99748.000000
nst z	29160.000000	157.682099	128.512524	0.000000	66.000000	116.000000	211.000000	929.000000
longitude	99749.000000	40.969569	121.855092	-179.997000	-72.102000	99.735000	142.794000	180.000000
depth	99464.000000	62.442085	108.755324	-4.000000	13.000000	33.000000	51.121750	700.000000
magNst	39781.000000	53.345919	78.841376	0.000000	12.000000	27.000000	60.000000	941.000000
gap	39453.000000	62.868549	38.592374	6.500000	36.000000	54.200000	80.000000	360.000000
latitude	99749.000000	3.443602	30.054950	-77.080000	-17.820000	-1.103000	29.423000	87.386000
depthError	50038.000000	8.094846	10.913250	-1.000000	2.400000	5.000000	9.800000	1091.900000
dmin	19514.000000	4.242374	5.130685	0.000000	1.269000	2.628000	5.139000	50.901000
horizontalError	18140.000000	7.672779	4.498657	0.000000	6.000000	7.500000	9.100000	99.000000
mag	99749.000000	5.453486	0.484780	5.000000	5.100000	5.300000	5.700000	9.500000
rms	71006.000000	0.965543	0.376917	-1.000000	0.820000	0.970000	1.100000	69.320000
magError	32770.000000	0.175678	0.156829	0.000000	0.060000	0.098000	0.230000	1.840000

Initially, the "Unnamed: 0" column contains the index numbers of the observations in the dataset. There are 99,749 observations, with indices ranging from 0 to 99,748. The mean index value is 49,874, and the standard deviation is 28,795.2. The minimum value is 0, while the maximum value is 99,748.

The "nst" column represents numerical estimates for earthquakes. These estimates have a mean of 157.68 and a standard deviation of 128.51. The minimum value is 0, and the maximum value is 929.

The "longitude" and "latitude" columns represent the longitude and latitude coordinates where the earthquake occurred. The mean longitude is 40.97, and the mean latitude is 3.44, indicating the geographical distribution of earthquakes.

The "depth" column represents the depth of the earthquake. The mean depth is 62.44, with a standard deviation of 108.76. The minimum depth is -4.0, and the maximum depth is 700.0, reflecting a wide distribution of earthquake depths.

The "magNst" column represents the number of stations used to estimate the earthquake's magnitude. The mean number of stations is 53.35, with a standard deviation of 78.84. These values provide insights into the reliability of magnitude estimates.

The "gap" column shows the azimuthal gap in the earthquake's coverage in a specific region. The mean gap is 62.87, with a standard deviation of 38.59. The minimum gap is 6.5, and the maximum gap is 360.0.

The "latitude" column represents the latitude coordinates where the earthquake occurred. The mean latitude value is 3.44, and the standard deviation is 30.05, indicating earthquakes occur in various latitudes worldwide.

The "depthError" column represents the error margin for depth estimates. The mean error is 8.09, with a standard deviation of 10.91. The minimum error is -1.0, and the maximum error is 1,091.9.

The "dmin" column shows the distance of the earthquake to the nearest station. The mean distance is 4.24, with a standard deviation of 5.13. The minimum distance is 0.0, and the maximum distance is 50.901.

The "horizontalError" column represents the horizontal error margin. The mean error is 7.67, with a standard deviation of 4.5. The minimum error is 0.0, and the maximum error is 99.0.

The "mag" column represents the earthquake's magnitude. The mean magnitude is 5.45, with a standard deviation of 0.48. The minimum magnitude is 5.0, and the maximum magnitude is 9.5.

The "rms" column represents the Root Mean Square (RMS) value, indicating measurement errors for the earthquake. The mean RMS is 0.97, with a standard deviation of 0.38. The minimum RMS is -1.0, and the maximum RMS is 69.32.

The "magError" column represents the error margin for magnitude estimates. The mean error is 0.18, with a standard deviation of 0.16. The minimum error is 0.0, and the maximum error is 1.84.

Data Analysis and Cleaning

Before analysis, columns with more than 20% missing values were removed. Missing values in the "Depth" and "Place" columns were filled with mean values. Additionally, underscores were replaced with spaces, and column names were standardized to uppercase.

1. *Univariate Analysis*
   a. *Magnitude and Depth Analysis*

The univariate analysis of the "Magnitude" feature in the earthquake dataset aims to examine the distribution of earthquake magnitudes. Magnitude is a parameter that measures the energy of an earthquake and is typically expressed using the Richter scale or Moment Magnitude Scale (Mw). The first step in the analysis is to create a histogram showing the general distribution of earthquake magnitudes. This histogram reveals the frequency of earthquakes occurring within specific magnitude ranges.

The depth distribution analysis explores the depths at which earthquakes typically occur. This analysis is used to understand the distribution of earthquakes at varying depths below the Earth's surface. It is shown in Figure 1.

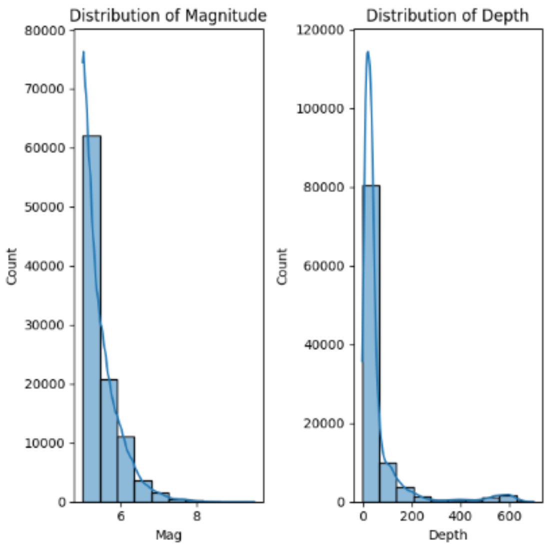

Figure 1. Univariate Analysis by Mag and Depth

b. *Type of Magnitude Distribution*

MB (Body Wave Magnitude) stands out as the type with the highest recorded magnitudes compared to other types. Several factors contribute to this: the type of wave used for measurement, the body wave, propagates through the Earth's interior. These waves can travel longer distances and provide more accurate results when measuring large earthquake magnitudes.

MB is particularly sensitive to larger earthquakes because it is calculated based on the amplitude of large body waves. This characteristic makes MB an ideal magnitude type for capturing and analyzing significant seismic events. It is shown in Figure 2.

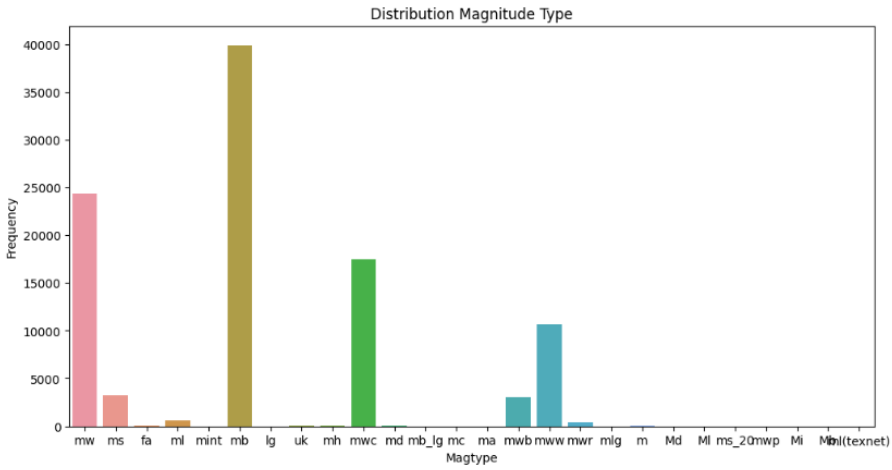

Figure 2. Distribution Mag Type

2. Bivariate Analysis

The bivariate analysis conducted on the earthquake dataset aims to examine the relationship between earthquake magnitudes and depths. This analysis seeks to classify earthquakes into specific depth ranges and identify potential connections between magnitude and depth.

The depth ranges are defined as follows:

- **Shallow earthquakes**: 0–70 km
- **Intermediate-depth earthquakes**: 70–300 km
- **Deep earthquakes**: Greater than 300 km

By categorizing earthquakes in this manner, the analysis provides insights into how depth influences the magnitude of seismic events, highlighting trends or patterns within each depth category. It is shown in Figure 3.

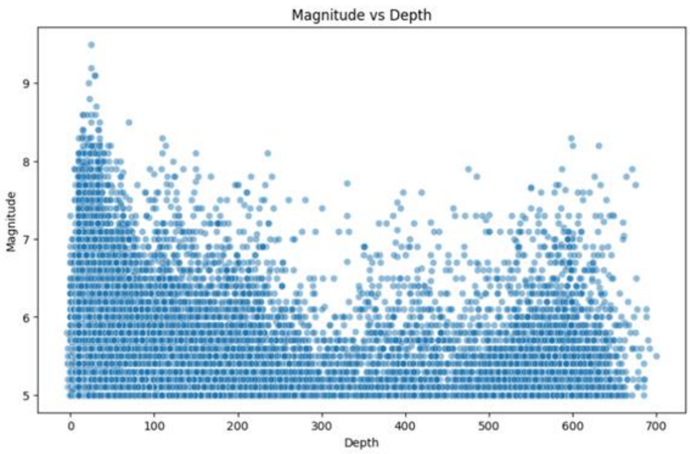

Figure 3. Magnitude vs Depth

3. Multivariate Analysis

In the multivariate earthquake analysis, the MB magnitude was utilized to derive insights into the intensity and potential impacts of seismic events. The findings indicated that using the MB magnitude provides more accurate and reliable information regarding the severity of earthquakes.

This magnitude type was selected to understand the relationships among various variables depicted in the graphical analysis. By incorporating multiple variables simultaneously, the analysis highlights complex interdependencies and patterns that contribute to a deeper understanding of earthquake dynamics. It is shown in Figure 4.

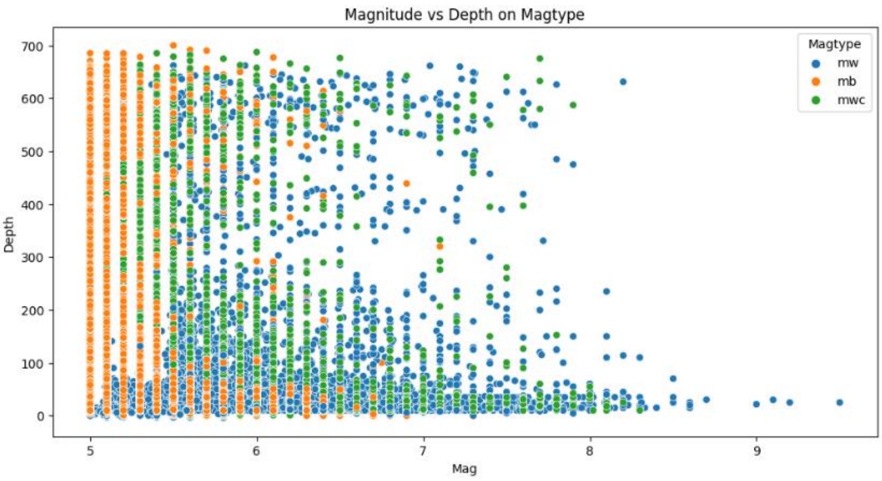

Figure 4. Magnitude vs Depth on Magtype

Feature Engineering

The following features were utilized in the model:

- **Latitude**
- **Longitude**
- **Depth**
- **Year**
- **Month**
- **Day**

These features represent the location, time, and depth of earthquakes, enabling the model to predict earthquake magnitudes effectively.

Creation of Training and Test Sets

The dataset was divided into training and test sets. The training set was used to train the model, while the test set was used to evaluate the model's performance. A split ratio of 80% for training and 20% for testing was applied using the train_test_split function.

Modeling

In this study, multiple machine learning models were employed to predict earthquake magnitudes. The models used are:

- **Random Forest Regressor**
- **Linear Regression**
- **Ridge Regression**
- **Lasso Regression**

For each model, training and prediction were performed using the sklearn library. The models' performance was evaluated using the Mean Squared Error (MSE) metric on the test set.

1) Random Forest Regressor

Random Forest is an ensemble method that combines multiple decision trees for prediction. In this study, the model was trained with 100 trees.

2) Linear Regression

Linear Regression models the linear relationship between dependent and independent variables. It serves as a fundamental regression technique.

3) Ridge Regression

Ridge Regression extends Linear Regression by adding an L2 penalty term to prevent overfitting. In this study, the penalty coefficient (alpha) was set to 1.0.

4) Lasso Regression

Lasso Regression adds an L1 penalty term to Linear Regression, aiming to prevent overfitting and perform feature selection by reducing some coefficients to zero. The penalty coefficient (alpha) was set to 0.1 in this study.

Prediction and Performance Evaluation

The performance of each model on the test set was evaluated using the MSE metric. Additionally, the predictions of each model were compared for two different location and depth combinations representing potential future earthquakes. It is shown in Table 3.

Tablo 3. Model Results

Model	Prediction 1	Prediction 2	Mean Squared Error (MSE)
Random Forest Regressor	5.317	6.3202	0.161
Lasso Regression	5.19975435	5.19900361	0.180
Linear Regression	5.19051159	5.18897125	0.182
Ridge Regression	5.1905116	5.18897126	0.182

Based on the performance evaluation of each model, the model with the lowest MSE was identified. The Random Forest Regressor exhibited the best performance, indicating its superior ability to predict future earthquake magnitudes. Further analysis was conducted to evaluate its predictive capability for potential future earthquakes.

V. RESULTS

A comprehensive analysis of earthquakes from geological, seismological, and engineering perspectives has fulfilled the primary objectives of this study. Hypotheses evaluating the effects of plate tectonics, volcanic activities, and human-induced triggers on earthquakes provided an in-depth understanding and unveiled critical relationships in these domains. The study emphasized the strategic importance of identifying risk profiles for geographic regions based on their earthquake potential, laying a scientific foundation for hazard analysis and risk assessment in earthquake-prone areas.

Detailed analyses under the effects of earthquakes shed light on the complex relationships between seismic activity and phenomena such as structural damage, tsunami generation, and landslides. The exploration of natural and artificial precursors, alongside the role and working principles of early warning systems, has contributed to a better understanding of these vital mechanisms.

The significant focus of this research, the application of machine learning and artificial intelligence technologies in earthquake risk analysis and prediction, serves as a potential guide for future studies. In this context, the study employed various machine learning models to predict earthquake magnitudes, yielding valuable insights into model training and performance.

The findings demonstrate that machine learning models hold considerable potential for predicting earthquake magnitudes. In particular, the Random Forest Regressor achieved the best performance, with the lowest MSE value, highlighting its superior accuracy in earthquake magnitude prediction.

By evaluating the preparedness of societies against earthquake risks, this study offers recommendations for proactive measures, shedding light on strategies to mitigate earthquake impacts. This research contributes a multidimensional analysis to the academic literature and emphasizes the role of data-driven approaches in improving disaster resilience.

VI. DISCUSSION

This study enhances the understanding of earthquake phenomena by integrating geological, seismological, and engineering perspectives. The findings confirm the complex interplay between natural and human-induced factors in seismic activity. The application of machine learning, particularly the Random Forest Regressor, demonstrates strong predictive potential, aligning with prior research. However, challenges remain in data quality and model generalization. The study also reinforces the importance of risk profiling, early warning systems, and mitigation strategies for disaster resilience. Future research should refine predictive models and expand datasets for improved earthquake forecasting.

VII. CONCLUSION

This study provides a comprehensive analysis of earthquake risks, highlighting the role of machine learning in seismic prediction. The Random Forest Regressor showed the highest accuracy, demonstrating its potential for improving risk assessment. Additionally, the study emphasizes the importance of early warning systems and preparedness strategies. While the findings are promising, further research is needed to enhance predictive models and broaden data integration.

REFERENCES

[1] M. Aamir, T. Ali, M. Irfan, A. Shaf, M. Z. Azam, A. Glowacz, F. Brumercik, W. Glowacz, S. Alqhtani, ve S. Rahman, "Natural Disasters Intensity Analysis and Classification Based on Multispectral Images Using Multi-Layered Deep Convolutional Neural Network," Sensors, vol. 21, no. 8, p. 2648, 2021, doi: 10.3390/s21082648.

[2] A. Ahmouda, H. H. Hochmair, ve S. Cvetojevic, "Analyzing the effect of earthquakes on OpenStreetMap contribution patterns and tweeting activities," Geo-Spatial Information Science, vol. 21, no. 3, pp. 195–212, 2018, doi: 10.1080/10095020.2018.1498666.

[3] A. T. Alisawi, P. E. F. Collins, ve K. A. Cashell, "Nonlinear Analysis of a Steel Frame Structure Exposed to Post-Earthquake Fire," Fire, vol. 4, no. 4, p. 73, 2021, doi: 10.3390/fire4040073.

[4] R. M. Allen ve A. Ziv, "Application of real-time GPS to earthquake early warning: REAL-TIME GPS AND EARTHQUAKE ALERTS," Geophysical Research Letters, vol. 38, no. 16, 2011, doi: 10.1029/2011GL047947.

[5] P. Anbazhagan, S. Srinivas, ve D. Chandran, "Classification of road damage due to earthquakes," Natural Hazards, vol. 60, no. 2, pp. 425–460, 2012, doi: 10.1007/s11069-011-0025-0.

[6] W. Astuti, W. Sediono, R. Akmeliawati, A. M. Aibinu, ve M. J. E. Salami, "Investigation of the characteristics of geoelectric field signals prior to earthquakes using adaptive STFT techniques," Natural Hazards and Earth System Sciences, vol. 13, no. 6, pp. 1679–1686, 2013, doi: 10.5194/nhess-13-1679-2013.

[7] C. Aydin ve V. Tecim, "Description Logic Based Earthquake Damage Estimation for Disaster Management," Anadolu University Journal of Science and Technology-A Applied Sciences and Engineering, vol. 15, no. 2, p. 93, 2015, doi: 10.18038/btd-a.01308.

[8] J. Bandibas ve S. Takarada, "Mobile Application and a Web-Based Geographic Information System for Sharing Geological Hazards Information in East and Southeast Asia," Journal of Geographic Information System, vol. 11, no. 3, pp. 309–320, 2019, doi: 10.4236/jgis.2019.113018.

[9] H. Bao, J.-P. Ampuero, L. Meng, E. J. Fielding, C. Liang, C. W. D. Milliner, T. Feng, ve H. Huang, "Early and persistent supershear rupture of the 2018 magnitude 7.5 Palu earthquake," Nature Geoscience, vol. 12, no. 3, pp. 200–205, 2019, doi: 10.1038/s41561-018-0297-z.

[10] R. Bendick ve R. Bilham, "Do weak global stresses synchronize earthquakes?," Geophysical Research Letters, vol. 44, no. 16, pp. 8320–8327, 2017, doi: 10.1002/2017GL074934.

[11] C. Can, G. Ergun, ve C. Gokceoglu, "Prediction of earthquake hazard by hidden Markov model (around Bilecik, NW Turkey)," Open Geosciences, vol. 6, no. 3, 2014, doi: 10.2478/s13533-012-0180-1.

[12] T. Chartier, O. Scotti, H. Lyon-Caen, ve A. Boiselet, "Methodology for earthquake rupture rate estimates of fault networks: Example for the western Corinth rift, Greece," Natural Hazards and Earth System Sciences, vol. 17, no. 10, pp. 1857–1869, 2017, doi: 10.5194/nhess-17-1857-2017.

[13] A. Cheaib, P. Lacroix, S. Zerathe, D. Jongmans, N. Ajorlou, M.-P. Doin, J. Hollingsworth, ve C. Abdallah, "Landslides induced by the 2017 Mw7.3 Sarpol Zahab earthquake (Iran)," Landslides, vol. 19, no. 3, pp. 603–619, 2022, doi: 10.1007/s10346-021-01832-0.

[14] J. Fang, C. Xu, Y. Wen, S. Wang, G. Xu, Y. Zhao, ve L. Yi, "The 2018 Mw 7.5 Palu Earthquake: A Supershear Rupture Event Constrained by InSAR and Broadband Regional Seismograms," Remote Sensing, vol. 11, no. 11, p. 1330, 2019, doi: 10.3390/rs11111330.

[15] X. Guo, B. Wei, G. Nie, ve G. Su, "Application of Mobile Signaling Data in Determining the Seismic Influence Field: A Case Study of the 2017 Mw 6.5 Jiuzhaigou Earthquake, China," International Journal of Environmental Research and Public Health, vol. 19, no. 17, p. 10697, 2022, doi: 10.3390/ijerph191710697.