Classifying and Forecasting Seismic Event Characteristics Using Artificial Intelligence

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Abstract

Seismic events present a significant global threat, underscoring the need for effective models to provide insights into these natural disasters. This paper addresses the critical need for advanced seismic event analysis by combining traditional data analysis with cutting-edge machine learning models. The primary objective is to develop models that classify seismic events into different types based on their geological and seismic characteristics and forecast their magnitude. The seismic activities categorized into groups by magnitude to enhance the understanding of these phenomena. Location-Based and Seismic Characteristics Features are utilized in seven machine learning models: Rule-Based Classifier, K-mean Classifier, Decision Trees, Random Forest, Support Vector Machines (SVM), k-Nearest Neighbors (kNN), and Logistic Regression. This approach aims to provide valuable insights into seismic activities, contributing to the development of more nuanced disaster analysis and early warning systems.

1. Introduction

The prevalence of natural disasters worldwide has highlighted the need for more advanced predictive models to understand and forecast these phenomena. Accurate disaster predictions can inform early warning systems, improve emergency response, and aid in disaster risk reduction. Among these catastrophic events, seismic activities such as earthquakes and nuclear explosions, are highly disruptive, requiring robust predictive models [1].

Seismic activities are influenced by numerous factors. These variables include the type of event (earthquake, nuclear explosion, or rock burst), geographic coordinates (latitude and longitude), and depth and magnitude of the event, among other factors [2]. However, predicting these occurrences involves more than just understanding the contributing factors; it requires the application of robust analysis techniques to interpret intricate patterns within the data.

There are two primary approaches to analyze seismic data: data analysis and machine learning. Data analysis applies statistical methods to seismic data to identify patterns, trends, and anomalies, and provides insights into the underlying processes that govern seismic activities. Data analysis uses past data such as earthquake magnitudes, depths, and occurrences to forecast future seismic events.

On the other hand, machine learning utilizes algorithmic models to analyze data and make predictions [3]. Various machine learning models have been proposed and employed in seismic studies, such as rule-based classifiers, K-means clustering, and Support Vector Machines (SVM) [4]. For instance, rule-based classifiers have been utilized to categorize earthquakes based on their distinct attributes. K-means clustering has been applied to cluster seismic events and pinpoint patterns that might elude traditional methods. Furthermore, Support Vector Machines have been employed not just for classifying the type of seismic events, but also for attempting to predict the severity of future events based on various geological and seismic features.

A groundbreaking study developed a hybrid AI model combining Inception v3 and XGBoost algorithms, augmented with SHAP values, for earthquake prediction in the Arabian Peninsula. This model, boasting an accuracy of 87.9%, underscored the critical need for incorporating diverse factors such as seismic gaps and tectonic contacts into prediction models, showcasing a leap forward in prediction accuracy and reliability.[5]

Further contributions in this field include innovative work on predicting the number and strength of earthquake aftershocks using machine learning models [6]. Another study discussed the next steps in earthquake forecasting with machine learning, highlights the development of detailed earthquake catalogs through the discrimination of foreshocks and aftershocks and forecasting the magnitude of expected earthquakes [7].

Additionally, a generalized deep learning approach for seismic activity prediction was demonstrated the efficacy of deep neural networks over traditional ML approaches. By leveraging feature engineering and deep learning techniques, this research introduced new features based on seismic laws, enhancing prediction models for various seismic regions, including Southern California, Chile, and the Hindu Kush [8].

A notable study from the University of Texas at Austin, as published in the Bulletin of the Seismological Society of America, explores AI's role in earthquake forecasting through a 30-week real-time case study in China. This research underlines the significant potential AI holds for enhancing the precision of earthquake predictions by leveraging big data and contributing to more effective seismic risk management strategies [9], [10].

Moreover, the integration of AI with acoustic technology by the American Institute of Physics marks a substantial leap towards creating an advanced tsunami early warning system. This innovative approach aimed to classify seismic events promptly and offered a rapid response mechanism to tsunami threats [11].

Another pivotal contribution to the domain is highlighted in a comprehensive review published in Sensors, focusing on the accuracy of real-time seismic intensity measurements (IMs) for earthquake early warning systems (EEWS). The study emphasizes the need for integrating various warning algorithms and enhancing the configuration of seismic station equipment. This approach is essential for advancing the construction of EEWS, demonstrating the potential for diverse methodologies in IMs prediction to significantly improve real-time seismic monitoring and alerts [12].

These studies collectively illustrate the potential of AI and ML in transforming seismic event prediction and analysis. By integrating sophisticated algorithms and diverse datasets, researchers are moving closer to more accurate and reliable earthquake prediction models, which are essential for mitigating the impacts of seismic events on communities worldwide.

The global prevalence of natural disasters underscores the importance of advanced analytical models to understand and manage these phenomena effectively. While accurate predictions can enhance early warning systems and disaster risk reduction strategies, the complexity of seismic activities necessitates a nuanced approach beyond simple occurrence prediction.

In this study, we aim to harness the synergy of data analysis and machine learning to develop models that enhance our understanding of seismic events. By focusing on the classification of seismic events and the forecasting of their characteristics based on a suite of predictors like depth, latitude, longitude, and other dataset features, we seek to provide valuable insights that contribute to more effective disaster preparedness and mitigation strategies.

2 Data and Preprocessing

As part of our study, we meticulously processed the data to derive meaningful features that could significantly enhance the predictive capability of our machine learning models. These features were divided into two primary categories: Location-Based Features and Seismic Characteristics Features [1].

2.1 Location-Based Features

Location-Based Features play a pivotal role in understanding the spatial dynamics of seismic events. These features are derived from the geographical coordinates—latitude and longitude—where each seismic event occurs, providing essential insights into the spatial distribution of these natural phenomena. To enhance the utility of these raw coordinates for machine learning analysis, we've developed two key derived features:

2.1.1 Latitude and Longitude Range

This feature represents the spatial extent of seismic activities within a specified geographical area. It helps in identifying potential seismic hotspots by measuring the range of latitude and longitude.

To assess seismic activity's dynamics, we calculate latitude and longitude ranges within defined time windows, capturing the spatial extent of events during these periods. This method underlines seismic hotspot shifts over time, essential for seismic analysis and regional preparedness.

$$\text{ForLatitudeRange:}\ \text{Max}(\text{Latitude})_{\text{T}} - \text{Min}(\text{Latitude})_{\text{T}}$$

$$\text{ForLongitudeRange:}\ \text{Max}(\text{Longitude})_{\text{T}} - \text{Min}(\text{Longitude})_{\text{T}}$$

2.1.2 Distance from Previous Event

The distance from previous event is calculated to quantify the geographical separation between consecutive seismic events. This metric is derived by computing the distance from the current event to its immediate predecessor, utilizing their latitude and longitude coordinates. This calculation is pivotal for understanding the movement patterns of seismic activities, as it reflects the spatial progression of events over time. This analysis is instrumental to identify potential seismic hotspots and understanding the geographical distribution of seismic events.

2.2 Seismic Characteristics Features

In our exploration, seismic characteristics features emerge as crucial for delving into the intrinsic properties of seismic events, such as their depth, magnitude, and other significant parameters. This

[1] https://drive.google.com/file/d/1ma3t2m9JeNkCi9gkqhwbrsWsri1WgRxL/view?usp=share_link

category encompasses a suite of derived features engineered to encapsulate the energy and intensity of seismic activities, thereby enhancing our analytical models.

2.2.1 Depth Range

The depth range quantifies the vertical extent of seismic activities, measuring the variance in depth across seismic events within a given data set. This calculation mirrors the methodology used for determining latitude and longitude ranges, adapting it to the vertical dimension. This feature helps in identifying patterns related to seismic event depths, such as whether deeper events correlate with other seismic characteristics like magnitude or geographical location.

2.2.2 Magnitude Variation

Magnitude variation tracks the changes in seismic intensity from one event to the next, providing a measure of how the strength of seismic events fluctuates over time. This feature is calculated by computing the difference in magnitude between consecutive seismic events. Capturing magnitude variation is essential for understanding the dynamics of seismic activity, as it can indicate emerging trends, potential aftershock sequences, or the stabilization of seismic activity after a significant event.

2.2.3 Seismic Energy

The seismic energy feature represents an estimation of the energy released by a seismic event, derived from its depth and magnitude. This composite feature offers a more comprehensive perspective on the event's potential destructiveness and impact. By combining depth and magnitude, this feature approximates the total energy output, which is crucial for understanding the scale of an event and its potential consequences. This understanding can aid in disaster preparedness and response planning, especially in regions prone to high-energy seismic activities.

2.2.4 Horizontal to Depth Ratio

This feature provides a geometric perspective on seismic events by calculating the ratio of the horizontal spread to the depth of an event. The horizontal to depth ratio offers insights into the shape and distribution of seismic activity, shedding light on the event's propagation and potential impact area. A higher ratio might indicate a seismic event with a wide impact area but shallow depth, while a lower ratio could signify a deeper, more focused event. This feature aids in the visualization and understanding of seismic events' structural characteristics, contributing to more nuanced seismic analysis and modeling.

Through these features, we aim to unravel the complex interplay of variables that characterize seismic events, paving the way for advanced predictive models and innovative disaster mitigation strategies.

3. Predictive Models and Results

3.1 Rule Based Classifier

The application of Rule 1 (R1) within our rule-based classification framework has demonstrated a substantive correlation between the magnitude of seismic events and their associated depths. Specifically, the rule stipulates that seismic events with a magnitude of 5.6 or greater are likely to have a depth of at least 15 kilometers.

An examination of the rule's performance, as illustrated in Figure 1, reveals that the actual correlation closely aligns with our predictions. With an accuracy of 74.72%, we observe that most seismic events that meet the magnitude threshold also adhere to the depth criterion posited by R1. This high level of accuracy reinforces the predictive power of the rule and suggests a strong, underlying geological relationship between the magnitude of an event and the depth at which it occurs.

Coverage, another critical metric, stands at 79.95%, indicating that R1 is relevant to a vast majority of the instances in our dataset. Such extensive coverage affirms the rule's utility and reliability in predicting the depth of seismic events based on their magnitude. The insights gleaned from this analysis are integral to enhancing our understanding of seismic patterns and, potentially, to improving early warning systems for seismic events of significant magnitude.

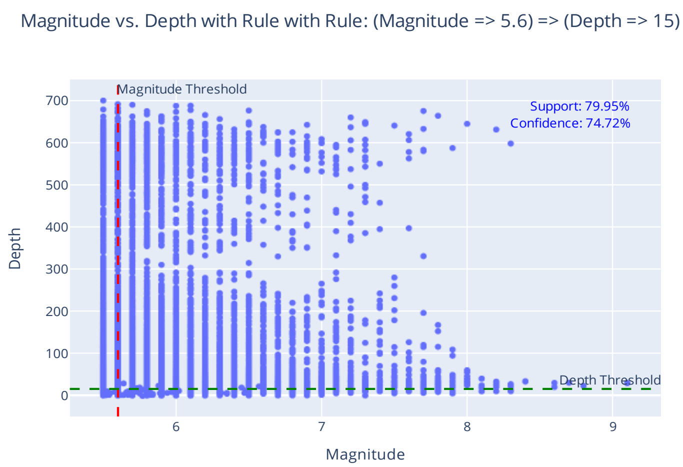

Figure 1. The correlation between earthquake magnitude and depth

The second rule, Rule 2 (R2), as depicted in Figure 2, was devised to reveal the spatial correlation between the longitude and latitude of seismic events. The rule shows that events with a longitude of -40 or greater are likely to exhibit a corresponding latitude of approximately -15.

The empirical analysis supported by the visualization indicates that Rule R2 has a confidence of 82.28%, meaning that in over 82% of cases where the rule was applicable, the seismic events did indeed follow the predicted latitude when the longitude condition was met. This high level of confidence reinforces the existence of a pronounced geographic pattern within the data.

Furthermore, the rule boasts a coverage of 67.56%, indicating its relevance to a substantial subset of the dataset. The visualization and corresponding metrics collectively demonstrate that Rule R2 offers a dependable predictive insight into the geographic distribution of seismic activities, affirming the rule's utility in understanding seismic event localization. The observed correlation suggests a potentially significant geological or geophysical rationale for such spatial consistency, warranting further investigation.

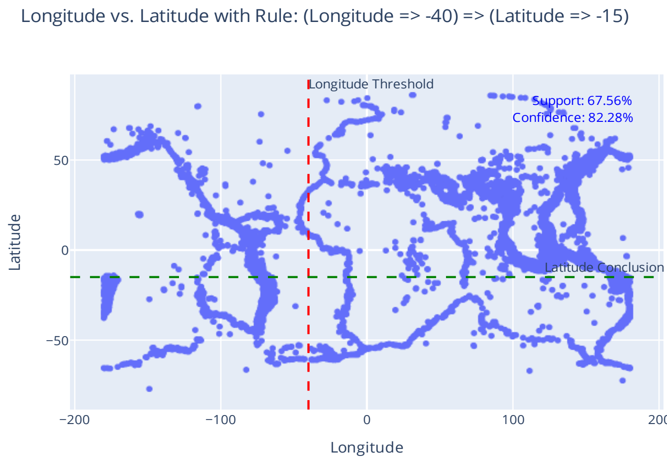

Figure 2. Geographic Distribution of Seismic Events

3.2 Decision Tree Classifier

We employed a decision tree classifier to predict the magnitude of seismic events based on geographical coordinates. The magnitude has been classified into four categories—Low, Medium, Strong, and Major—corresponding to the following bins: [0, 5.5, 6.5, 7.5, 10].

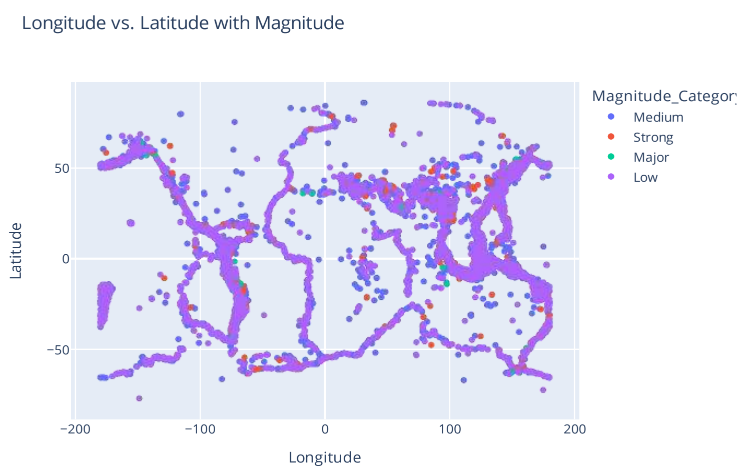

Figure 3: Global Seismic Activity by Magnitude

Figure 3 shows the relationship between the locations (latitude and longitude) and the categorized magnitudes of seismic events. Each color represents a different magnitude category, providing a clear visual distinction between varying levels of seismic intensity.

The decision tree's predictions, based on latitude and longitude, are encapsulated in a set of rules. For example, one rule indicates that seismic events with a latitude less than -17.40 and longitude less than -178.11 are most likely to be categorized as Medium. In contrast, events with a latitude greater than -11.14 and longitude less than 140.56 tend to be classified as Strong.

The classifier's accuracy stands at 72%, with a particularly high precision for medium magnitude events, indicates a reliable identification of this category in the test data. However, the low recall and precision for Low and Strong categories suggest that these are less accurately predicted, as reflected in the confusion matrix (Figure 4).

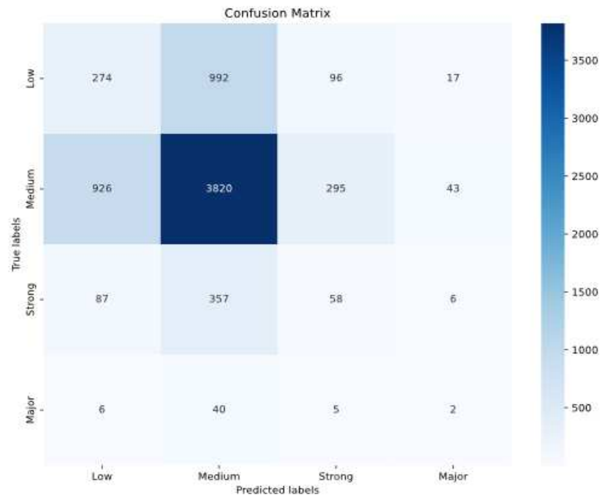

Figure 4: Confusion Matrix for Decision Tree

The confusion matrix reveals the classifier's tendency to predict the most events as Medium. This analysis offers valuable insights into the geographical distribution of seismic event magnitudes and presents a predictive model that could be refined further for more balanced accuracy across all categories. The decision tree's rules, along with the model's quantitative performance metrics, contribute to a deeper understanding of the spatial characteristics influencing seismic magnitudes.

3.3 K-mean Clustering

K-means is focusing on the intricate relationship between the magnitude and depth of the events. The process was informed by an elbow curve analysis, which helped determine the optimal number of clusters to use. As illustrated in the K-means clustering plot (Figure 5), ten distinct clusters were identified. Each cluster indicates different geological conditions or seismic events based on their depth and magnitude characteristics. The consistency of clusters provides a robust foundation for further analysis, potentially enriching seismic risk assessment models and aiding in the prediction of seismic hazards.

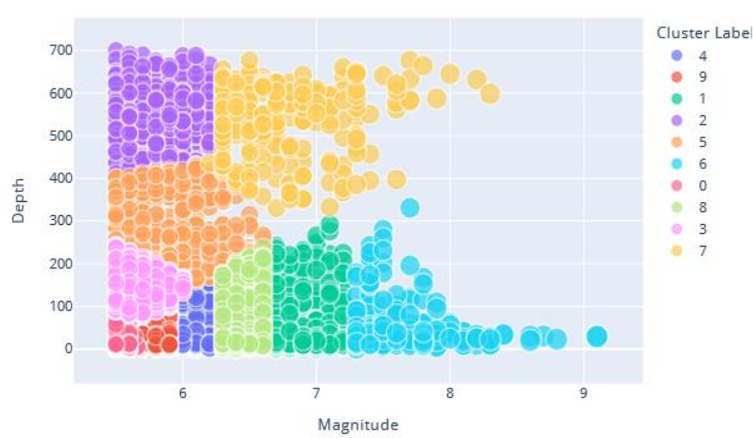

Figure 5: Scatter Plot with K-Means Clustering on Seismic Data

3.4 Support Vector Machine

Support Vector Machine (SVM) models used to classify the earthquake data based on depth and magnitude attributes. Four different SVM models with linear, polynomial, Radial Basis Function (RBF), and sigmoid kernels were constructed.

SVM model with linear kernel outperformed the other models, achieving a near-perfect accuracy score of 0.9994. This high degree of accuracy indicates that the linear kernel SVM model demonstrated the best performance among the four models in terms of classifying the earthquake data.

The SVM models utilizing polynomial, RBF, and sigmoid kernels all returned an identical accuracy score of 0.9929. Despite this score being slightly lower than linear SVM, it is still significantly high, implying that these models also offer strong performance in predicting earthquake data.

Overall, the results from the SVM models strongly suggest that the linear kernel model is the most effective for the classification of earthquake's depth and magnitude attributes. Notably, SVM's robustness and performance provides insights into the relationships between depth and magnitude. This outcome further supports our ability to predict and understand seismic events accurately and efficiently.

3.5 Model Comparison

In assessing the efficacy of various classifiers in predicting earthquake magnitudes based on geographical coordinates, we conducted a comparative analysis using several machine learning models. Rule Based Classifier, K-Mean, Decision Trees, Random Forest, Support Vector Machines (SVM), k-Nearest Neighbors (kNN), and Logistic Regression were applied to a dataset of latitudes and longitudes associated with seismic events.

The Decision Tree classifier offers a simple, interpretable model that forms decision paths based on feature values. Random Forest, an ensemble of decision trees, typically improves prediction accuracy through averaging and is less prone to overfitting. SVMs are robust to outliers and optimal for non-linear boundaries, while kNN uses proximity to vote for classifications. Logistic Regression, although simple, is effective for binary outcomes and provides probabilities for the predictions.

The performance metrics plotted—Accuracy, Precision, Recall, and F1 Score—present a comprehensive picture of each model's strengths. Accuracy measures the proportion of total correct predictions. Precision indicates the correctness of positive predictions. Recall assesses the coverage of actual positive cases, and the F1 Score provides a balance between precision and recall, for uneven class distributions.

From the results depicted in the provided plot (Figure 6), it's evident that the classifiers exhibit varying degrees of performance across these metrics. The final choice of classifier may depend on the specific needs of the earthquake magnitude prediction task, whether it's the overall accuracy or the balance between false positives and false negatives as dictated by the Precision-Recall tradeoff.

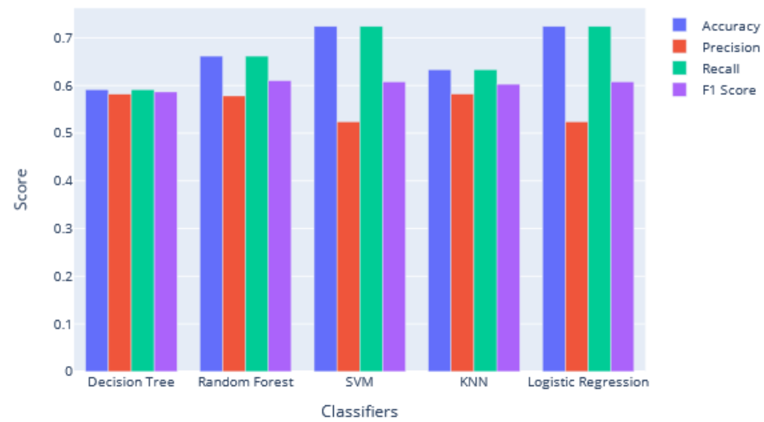

Figure 6: Decision Tree, Random Forest, SVM, kNN, and Logistic Regression Models' Comparison.

Conclusion

This project underscores the profound potential of machine learning techniques in the realm of seismology. By leveraging K-mean clustering model, we've delineated distinct seismic event patterns, enhancing our grasp of the intricate relationship between an earthquake's depth and magnitude. The SVM classifier offers robust accuracy in forecasting seismic occurrences.

Combining these advanced AI tools with traditional analysis has yielded a synergistic effect, amplified our understanding of seismic dynamics, and improved our hazard assessment capabilities. This integrative approach has not only reinforced the predictive framework for seismic events but also charted a course for future research dedicated to the refinement of these prediction models.

As we look ahead, the insights procured from this comprehensive analysis pave the way for continued innovation in seismic event prediction. Through ongoing research, validation, and interdisciplinary collaboration, we aim to enhance the precision of these models, contributing to the global effort of disaster preparedness and seismic risk reduction. Our endeavor remains steadfast in advancing seismic research, as we attempt to fortify our defenses against the capricious nature of earthquakes and contribute to the safety and security of vulnerable communities worldwide.

Declaration

Data Availability

The datasets generated and/or analyzed during the current study are available in the repository:

https://drive.google.com/file/d/1ma3t2m9JeNkCi9gkqhwbrsWsri1WgRxL/view?usp=share_link

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