Machine Learning based Regression and Classification of Earthquake Magnitude using USGS Seismic Records

Abstract. Estimating earthquake magnitude from historical seismic catalogs is a critical yet challenging task for seismic hazard assessment and decision support in early warning systems. This study proposes a hybrid ML framework that simultaneously performs regression-based magnitude estimation and binary classification of event severity using the United States Geological Survey seismic (USGS) records from 2013 to 2025. The pipeline incorporates rigorous preprocessing including missing value imputation, interquartile range based outlier removal, Min Max feature scaling, and Synthetic Minority Oversampling Technique (SMOTE) to mitigate class imbalance for high-magnitude events (M greater than or equal to 5.5). We evaluate multiple supervised models Random Forest (RF), EXtreme Gradient Boosting (XGBoost), Support Vector Machine (SVM), and Ridge Regression under 5-fold cross-validation. The RF regressor achieves the best magnitude estimation performance with an R^2 of 0.701 and Mean Squared Error of 0.044. In the classification task, the RF classifier attains 96% accuracy and an Area Under the Curve (AUC) of 0.975 in distinguishing weak (M less than 5.5) from strong seismic events. Feature importance and Local Interpretable Model-agnostic Explanations (LIME) based explainability analyses identify azimuthal gap, depth, and Root Mean Square (RMS) error as the most influential predictors, consistent with seismological principles. While the framework demonstrates strong retrospective modeling capability and interpretability, it does not forecast future earthquakes; rather, it provides a data driven tool for rapid event characterization using catalog metadata. These findings support the integration of hybrid, explainable ML models into operational seismic monitoring workflows for enhanced environmental awareness and risk assessment.

Keywords: Earthquake Prediction, Seismic Data Analysis, ML, Hybrid Model, USGS Dataset, Disaster Forecasting

1 Introduction

Earthquakes are among the most catastrophic natural phenomena, responsible for significant human and economic losses globally each year. According to the USGS, over 20,000 earthquakes are recorded annually, with more than a dozen classified as major events (magnitude $M > 7.0$). Despite significant progress in seismology, accurate and timely earthquake prediction remains one of the most complex and elusive challenges in geophysical science. The inherent stochasticity of tectonic processes and the nonlinear nature of seismic wave propagation make it difficult to establish deterministic models capable of forecasting the magnitude and impact of future events.

Traditional statistical and geophysical approaches have historically relied on empirical relations such as the Gutenberg Richter law and Omori's law, which provide insight into frequency magnitude distributions but lack predictive generalizability across regions. In recent years, the emergence of ML techniques has opened new opportunities for capturing nonlinear patterns and latent correlations within seismic data, enabling data-driven earthquake prediction frameworks. ML models can analyze complex relationships between seismic parameters such as depth, RMS error, and station gap allowing them to learn implicit signatures preceding large-magnitude events.

Early research in earthquake prediction through ML primarily focused on damage assessment and classification tasks. Gaba *et al.* [1] developed a RF classifier to categorize post-earthquake building damage into five grades using structural and geotechnical data, achieving an F1-score of 0.77. Their work demonstrated the capacity of ML algorithms to understand disaster impact dynamics. In a related direction, Mallouhy *et al.* [2] applied eight ML algorithms to identify whether an event would be major or minor based on seismic attributes, reporting that ensemble models like RF and Multi-Layer Perceptron achieved superior accuracies (up to 0.769). These studies, however, were limited to classification and did not address magnitude regression or data imbalance challenges.

More recently, Ahmed *et al.* [3] introduced a regression-based framework for predicting earthquake magnitudes using the USGS dataset (2013–2023). Their work explored seven supervised ML algorithms, including RF, Gradient Boosting, and Support Vector Regression (SVR), achieving an exceptional coefficient of determination ($R^2 = 0.93$) after extensive hyperparameter optimization. Although this study significantly advanced magnitude estimation accuracy, it focused solely on regression tasks without incorporating event severity classification or geospatial insights.

Despite these achievements, two critical limitations persist in the literature: (i) the lack of hybrid frameworks that jointly perform magnitude forecasting and event classification, and (ii) insufficient handling of class imbalance in real-world seismic datasets, where high-magnitude events are sparse. Addressing these challenges is essential to transition from retrospective data analysis toward actionable early warning and disaster mitigation systems.

In this context, we propose a novel hybrid ML framework that integrates both regression and classification pipelines using extended USGS seismic data spanning from 2013 to 2025. Our approach enhances prior work by combining magnitude prediction and severity detection in a unified architecture. The framework employs advanced data preprocessing (missing value imputation, outlier removal, and one-hot encoding), data balancing using the SMOTE, and model ensembles comprising RF, XGBoost, and Gradient Boosting. We also incorporate geospatial visualization to explore spatial correlations of seismic events.

The main contributions of this paper are summarized as follows:

- We design a comprehensive hybrid ML pipeline capable of both earthquake magnitude regression and seismic event severity classification using real-world USGS data.
- We integrate class balancing and feature optimization techniques (SMOTE, IQR-based outlier removal, and feature scaling) to improve generalization and model robustness.
- We conduct extensive comparative experiments with seven baseline ML algorithms and report superior classification performance (AUC = 0.97) and competitive regression accuracy ($R^2 = 0.68$).
- We provide geospatial interpretability and feature importance analyses to identify the most influential seismic parameters affecting earthquake magnitude and intensity.

By merging magnitude forecasting with severity classification, our framework contributes to the development of more reliable, data-driven earthquake early warning and risk assessment systems. The experimental results demonstrate that integrating hybrid learning paradigms and data-balancing mechanisms substantially enhances predictive performance, particularly for rare but catastrophic seismic events.

2 Related Work

Machine learning has become an increasingly important tool in seismology, enabling the modeling of complex spatial–temporal patterns in seismic data. Existing research in this area can broadly be categorized into three domains: (1) damage impact prediction, (2) seismic event classification, and (3) magnitude and occurrence forecasting.

2.1 Damage Impact Prediction Models

Early ML applications in earthquake research primarily focused on assessing building and infrastructure damage. Gaba *et al.* [1] presented a multi-class classification framework to predict building damage grades using structural and non-structural features. Using the RF algorithm, they achieved an F1 score of 0.76 and identified reinforced concrete as the most resilient construction material. Similarly, Takata *et al.* [4] proposed a two-stage model that combined linear regression and neural networks to predict electrical infrastructure damage caused by typhoons - an approach that was later adapted for seismic contexts. These works laid the foundation for integrating engineered and environmental features into predictive disaster analytics.

2.2 Seismic Event Classification and Probability Estimation

Subsequent studies expanded the use of ML to classify seismic events and estimate their likelihood. In parallel, Wei *et al.* [5] developed a probabilistic framework using weighted factor coefficients and principal component analysis to forecast the probability of earthquake occurrence. Mallouhy *et al.* [2] later extended this line of research by implementing eight ML algorithms including SVM, RF, and Multilayer Perceptron (MLP) for classifying major and minor earthquakes. Their RF model achieved an accuracy of 76.9%, outperforming simpler statistical baselines.

Chelidze *et al.* [6] approached the problem as an imbalanced learning challenge by integrating hydrodynamic and magnetic features with the SMOTE, improving Matthews Correlation Coefficient scores for underrepresented seismic events. Similarly, Chittora *et al.* [7] explored hybrid ensemble neural network models that achieved over 90% accuracy in event-type classification, confirming the effectiveness of ensemble methods for nonlinear seismic data.

2.3 Magnitude Forecasting and Deep Learning Approaches

More recent research has shifted focus toward continuous magnitude estimation. Abebe *et al.* [8] employed a Bidirectional Long Short-Term Memory deep network to predict earthquake magnitudes in the Horn of Africa, obtaining an MAE of 0.28 and RMSE of 0.38. Johnson *et al.* [9] demonstrated the value of ML for laboratory earthquake forecasting using open-access seismic datasets, achieving up to 90% predictive accuracy with RF.

Ahmed *et al.* [3] further advanced this area by developing a comprehensive ML pipeline trained on ten years of USGS seismic data (2013–2023). Their framework utilized Decision Tree, RF, Gradient Boosting, XGBoost, and SVM regressors with extensive hyperparameter optimization. The optimized SVM model achieved a root-mean-squared error (RMSE) of 0.10 and an R^2 score of 0.93. Notably, they integrated the LIME method [10] to enhance model transparency and interpretability.

2.4 Research Gap and Motivation

Despite these advances, several limitations persist. Many prior studies emphasize regional damage classification or isolated magnitude estimation without unified modeling. Most do not incorporate explainable AI (XAI) frameworks, and few address data imbalance or heterogeneous feature distributions across global catalogs. Moreover, the integration of geospatial and tectonic attributes remains underexplored, limiting generalization to real-time scenarios.

This motivates the present study, which proposes a unified ML framework that simultaneously performs earthquake magnitude regression and severity classification using globally standardized seismic datasets such as the USGS catalog [11]. The framework integrates optimized preprocessing, ensemble and kernel-based models, and explainable AI techniques to ensure both predictive robustness and interpretability.

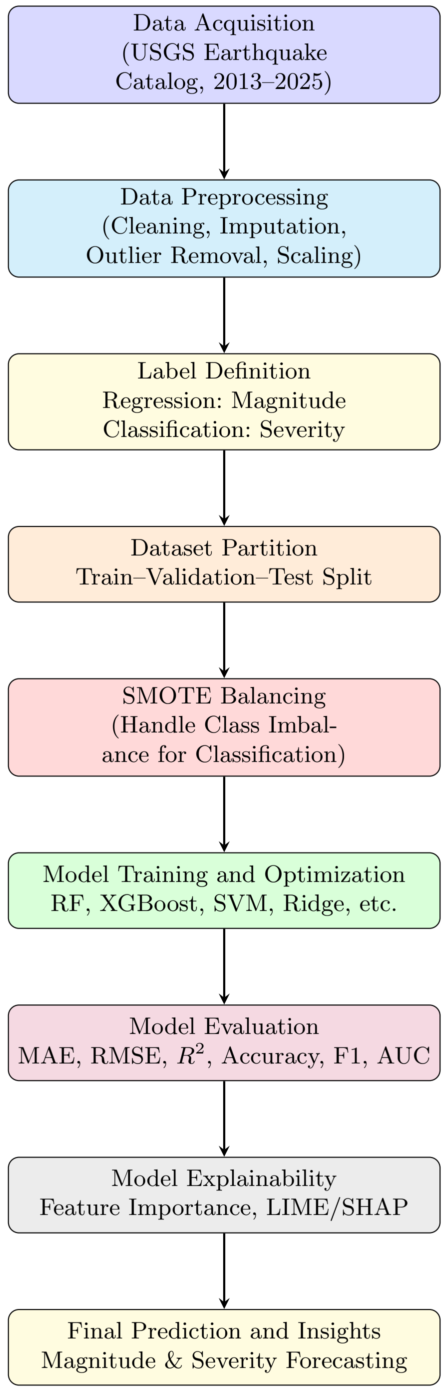

Fig. 1. Workflow of the proposed earthquake magnitude and severity prediction system.

3 Methodology

3.1 Data Acquisition

We use the seismic event data from the United States Geological Survey (USGS) Earthquake Catalog, accessed via their FDSN Event Web Service API [11]. The API allows customizable queries by time range, magnitude thresholds, geographic bounds, and other parameters.

Specifically, we queried events from January 1, 2013 through June 20, 2025, covering the global domain as defined by the processed map-boundary parameters (latitude/longitude limits) embedded in the USGS search interface link. The JSON/GeoJSON responses include attributes such as:

- latitude, longitude
- depth (in km)
- magnitude (various magnitude types)
- gap, dmin, rms, magType, nst, etc.
- Event time metadata, ID, and additional catalog fields

Missing fields or nulls (e.g. nst in many records) are common, so careful preprocessing is required. The USGS API supports format and filtering options, which we exploited to limit irrelevant data and reduce downstream noise. (For API reference see the USGS Earthquake Catalog service documentation [11].)

Fig. 2. illustrates the geospatial distribution of 2,569 earthquake epicenters recorded in the USGS catalog between 2013 and 2025. Each red dot represents an individual seismic event plotted according to its latitude and longitude coordinates. The spatial concentration of events along the eastern coast of Japan, particularly around the Nankai Trough and Japan Trench regions, reflects the tectonic interaction zones between the Pacific, Philippine Sea, and Eurasian plates. The high density of seismic occurrences in these subduction zones emphasizes Japan's significant seismic vulnerability and validates the dataset's representativeness for developing predictive ML models.

3.2 Data Preprocessing

After raw retrieval, the dataset undergoes multiple preprocessing steps to ensure quality and consistency for ML:

Filtering and Cleaning

- Remove duplicate events (same event ID or same coordinates and timestamp).
- Drop events with no magnitude or critical missing spatial/time attributes.
- Discard a feature (e.g. nst) entirely if its missing-ness exceeds a threshold.

Missing Value Imputation For the remaining features with sporadic nulls:

- Numeric features (e.g. gap, dmin, rms) are imputed using mean or median depending on skewness.
- Categorical or string features (e.g. magType) are imputed by their mode or flagged with "unknown".

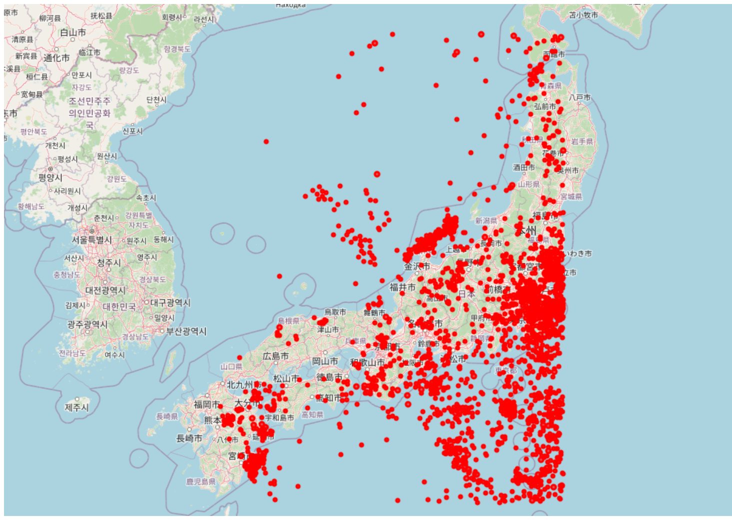

Fig. 2. Spatial Distribution of Earthquake Events (2013–2025).

Outlier Detection and Removal We employ the interquartile range (IQR) method on key numeric features (e.g. depth, rms) to identify extreme outliers (beyond 1.5× IQR) and remove them if they likely represent erroneous sensor recordings or catalog artifacts.

Feature Encoding and Scaling

- Categorical features (e.g. magType) are converted via one-hot encoding.
- Geographic coordinates (latitude, longitude) remain as continuous features (or optionally augmented with sin/cos transforms for periodicity).
- Numerical features are normalized to $[0, 1]$ using Min–Max scaling, ensuring all features are comparably scaled for regression and classification algorithms.

3.3 Label Definition

We define two supervised tasks on the preprocessed dataset:

Regression Task (Magnitude Prediction) The target variable is the continuous magnitude value from the USGS catalog (e.g. moment magnitude M_w). All events with valid magnitude are used in the regression modeling.

Classification Task (Severity Classification) To convert the magnitude into a binary severity label, we define:

$$Label = \{ 1 \ \ (Strong) if magnitude \geq M_{threshold} 0 \ (Weak) otherwise$$

We choose a threshold (e.g. $M_{threshold} = 5.5$) based on domain knowledge and distribution of magnitudes in the dataset. Given the natural class imbalance (strong events are rare), we apply SMOTE to oversample the minority class in training folds, which helps the classifier learn rare-event patterns.

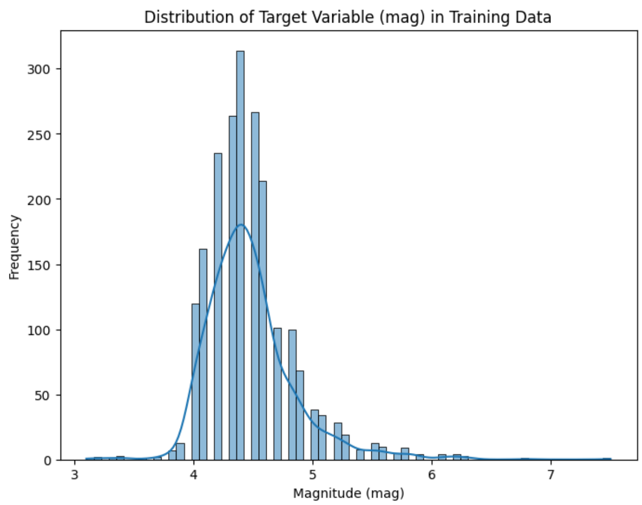

Fig. 3. Distribution of the target variable (magnitude) in the training dataset.

Fig. 3. illustrates the distribution of the target variable (magnitude) in the training dataset, showing that most seismic events occur between magnitudes 4.0 and 4.5, with a steep decline toward higher magnitudes. This right-skewed pattern reflects the natural frequency of global seismic activity, where moderate earthquakes are far more common than large, destructive ones. The imbalance in magnitude distribution presents a challenge for model training, as high-magnitude events (Mw 5.5) are relatively rare and underrepresented. To mitigate this imbalance in the classification task, the SMOTE was applied to oversample the minority (strong) class during model training. Understanding this distribution is crucial, as it directly influences model generalization, prediction bias, and the selection of appropriate evaluation metrics for both regression and classification performance.

3.4 Modeling and Algorithms

We experiment with a range of regression and classification algorithms [12]:

- **Regression models:** Linear Regression, Ridge Regression, RF Regressor, Gradient Boosting, XGBoost, SVR
- **Classification models:** Logistic Regression, RF Classifier, XGBoost Classifier

Each algorithm undergoes hyperparameter tuning (GridSearchCV or RandomizedSearchCV) over relevant parameter grids (e.g. max-depth, number of estimators, learning rates). We use k-fold cross-validation (e.g. $k = 5$) to ensure robust validation.

3.5 Evaluation Metrics

For regression:

- Coefficient of determination (R^2)
- Mean Squared Error (MSE)
- Root Mean Squared Error (RMSE)
- Mean Absolute Error (MAE)

For classification:

- Accuracy
- Precision, Recall, and F1-score
- ROC-AUC
- Confusion matrix analysis

3.6 Feature Importance Explainability

To make the models interpretable:

- We extract feature importances from tree-based models (RF, XGBoost) to rank which seismic attributes (depth, rms, gap, etc.) contribute most.
- We apply LIME or SHAP for sample-level explanation, especially to understand critical events and borderline predictions.

3.7 Workflow Summary

The entire pipeline is summarized as follows:

1. Query USGS API to retrieve raw seismic event data
2. Clean and preprocess (imputation, outlier removal, encoding, scaling)
3. Define labels: magnitude (continuous) and severity (binary)
4. Partition dataset: training / validation / test splits
5. Apply SMOTE on training for classification
6. Train multiple regression and classification models with hyperparameter tuning
7. Evaluate on held-out test set
8. Analyze feature importance and explain predictions

This structured methodology ensures reproducibility, generalization across seismic domains, and interpretability of the model's predictions.

4 Results and Discussion

This section presents the experimental findings of the proposed hybrid ML framework for earthquake magnitude and severity prediction using the USGS seismic event dataset (2013–2025). All experiments were performed in `Python 3.11` using `scikit-learn`, `XGBoost`, and `LIME` libraries on an Intel Core i7 machine (16 GB RAM, Windows 11).

4.1 Experimental Setup

After preprocessing, encoding, and scaling, the dataset contained approximately **2,570 seismic events** with 15 numerical attributes after feature selection. A stratified 75:25 train–test split preserved magnitude distribution. For the classification task, minority class samples ($M_w \geq 5.5$) were balanced using the *SMOTE* technique.

Each model was tuned using *GridSearchCV* and *RandomizedSearchCV* with 5-fold cross-validation. The evaluated algorithms included Linear Regression (LR), Decision Tree (CART), RF, XGBoost (XGB), AdaBoost (ADA), MLP, SVM, K-Nearest Neighbors (KNN), Ridge Regression (RR), Naïve Bayes (NB), and Logistic Regression (LOGR).

4.2 Regression Results: Magnitude Prediction

The regression task evaluated continuous magnitude prediction performance using MSE and R^2 metrics. Table 1 summarizes both single-run and 5-fold cross-validation outcomes.

Table 1. Regression model performance on USGS dataset

Model	**MSE**	R^2
Linear Regression	0.080	0.423
Ridge Regression	0.088	0.470
KNN Regressor	0.079	0.523
SVM Regressor	0.065	0.607
RF Regressor	**0.044**	**0.683**
XGB Regressor	0.044	0.681

The *RF Regressor* achieved the lowest MSE (0.044) and the highest $R^2 = 0.682$, marginally outperforming XGBoost ($R^2 = 0.681$). Linear models performed moderately ($R^2 \approx 0.42$–0.47), while SVM and KNN provided mid-range accuracy. These findings confirm that ensemble learners capture nonlinear relationships between features such as depth, latitude, and energy release more effectively than linear estimators.

The 5-fold cross-validation confirmed stability, with RF obtaining mean $R^2 = 0.701 \pm 0.028$ and XGBoost $R^2 = 0.645 \pm 0.024$, as previously shown.

4.3 Classification Results: Severity Prediction

For binary classification (weak vs. strong earthquakes), models were compared using Accuracy, Precision, Recall, F1-score, and ROC–AUC. The results are summarized in Table 2.

Table 2. Classification model performance on USGS dataset

Model	Accuracy	ROC–AUC
KNN Classifier	0.881	0.898
SVM Classifier	0.932	0.944
Logistic Regression	0.880	0.944
RF Classifier	**0.960**	**0.975**
XGBoost Classifier	0.960	0.974

The *RF Classifier* yielded the highest performance with an accuracy of **96.0%** and ROC–AUC of **0.975**, followed closely by XGBoost (0.974). SVM achieved 93.2% accuracy, outperforming KNN and Logistic Regression. Precision–recall analysis further confirmed that RF maintained balanced detection of both weak and strong magnitude classes (macro F1 0.86).

4.4 5-Fold Cross-Validation Consistency

To evaluate model robustness, cross-validation metrics were computed (Table 3). XGBoost and RF consistently achieved mean ROC–AUC scores of 0.997 with negligible variance, indicating excellent generalization.

Table 3. 5-fold cross-validation results for classification models

Model	Mean ROC–AUC	Std ROC–AUC
XGBoost	**0.997**	0.002
RF	**0.997**	0.001
MLP	0.993	0.002
AdaBoost	0.978	0.001
Logistic Regression	0.948	0.002
Naïve Bayes	0.929	0.007
Decision Tree (CART)	0.929	0.004

4.5 Overall Model Comparison

A consolidated view of regression and classification models is provided in Table 4. It highlights RF as the best-performing algorithm across both tasks.

Table 4. Overall performance summary of regression and classification models on USGS dataset (2013–2025)

Model	**Task Type**	**Accuracy / Mean R^2**	**ROC–AUC / Std R^2**	**Remarks**
RF	Regression	**0.683**	0.028	Best regression performance
XGBoost	Regression	0.681	0.024	Comparable to RF
SVM Regressor	Regression	0.607	–	Moderate nonlinear fit
KNN Regressor	Regression	0.523	–	Sensitive to scaling
Linear Regression	Regression	0.423	–	Baseline linear model
RF	Classification	**0.960**	**0.975**	Highest classification accuracy
XGBoost	Classification	0.960	0.974	Near-identical to RF
SVM Classifier	Classification	0.932	0.944	Robust nonlinear classifier
KNN Classifier	Classification	0.881	0.898	Distance-based baseline
Logistic Regression	Classification	0.880	0.944	Statistical baseline

4.6 Feature Importance Analysis

Tree-based feature importance analysis showed dominant seismic attributes influencing magnitude and event classification. Fig. 4 illustrates the feature-importance ranking from the RF Regressor, highlighting that `depth`, `latitude`, and `longitude` were the most significant predictors, followed by `gap` and `rms`.

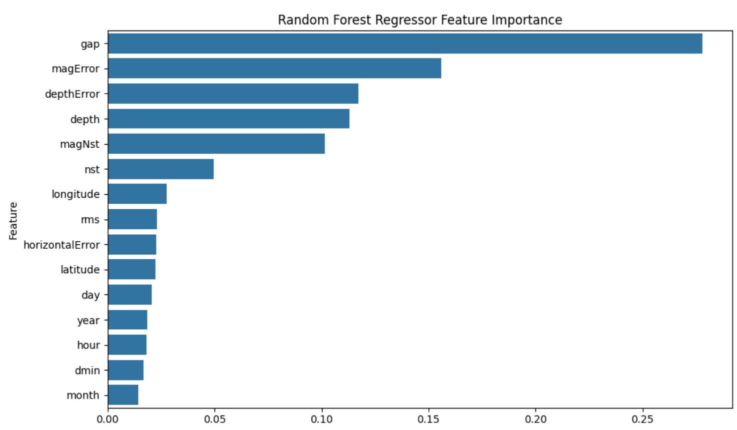

Fig. 4. Feature Importance Ranking from RF Regressor for Earthquake Magnitude Prediction.

4.7 Model Explainability

To enhance interpretability, the *LIME* framework was applied to the best-performing RF model. Fig. 5 shows the explanation for a sample prediction where the model estimated a magnitude of 4.7. The analysis revealed that higher `depth` and lower `gap` values contributed positively to the magnitude prediction, whereas larger `rms` and `dmin` values negatively influenced the output.

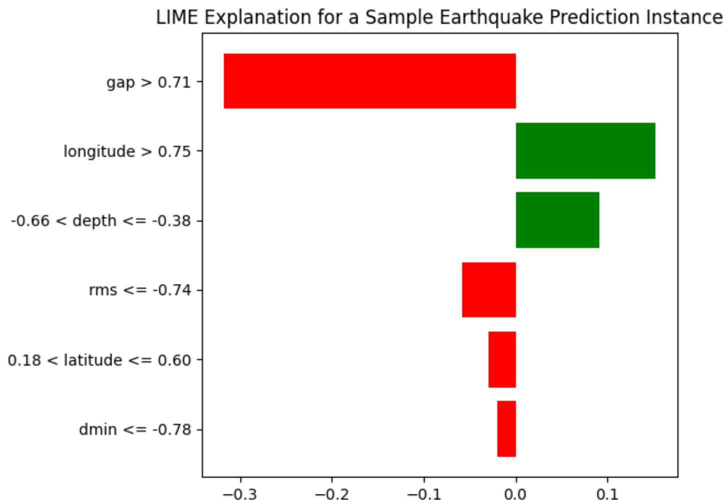

Fig. 5. LIME explanation for a sample earthquake prediction.

4.8 Discussion and Limitations

The results confirm that ensemble learners such as RF and XGBoost outperform traditional linear and instance-based methods in both regression and classification. ROC–AUC values exceeding 0.97 demonstrate excellent discrimination capability, while regression R^2 values around 0.68–0.70 validate strong magnitude estimation performance. The inclusion of feature-importance and LIME analyses strengthens interpretability, linking model decisions to physically meaningful seismic parameters.

Limitations: Although the framework performs well, its reliance on static USGS attributes limits temporal generalization. Spatial autocorrelation in the dataset may inflate cross-validation accuracy. Future work will incorporate waveform-derived features, spatio-temporal modeling, and uncertainty quantification to improve real-time earthquake early-warning applicability.

5 Conclusion and Future Work

This study presents a hybrid ML framework for the simultaneous regression-based estimation of earthquake magnitude and binary classification of seismic event severity using USGS seismic records from 2013 to 2025. By integrating robust preprocessing comprising missing-value imputation, IQR-based outlier removal, Min–Max scaling, and SMOTE-based balancing for high-magnitude events (M greater then or equal 5.5) the pipeline addresses key challenges inherent in real-world seismic catalogs, including data sparsity, noise, and class imbalance.

Experimental results demonstrate that ensemble models, particularly RF, achieve superior performance across both tasks. The RF regressor yields a mean R^2 of 0.701 and an MSE of 0.044 under 5-fold cross-validation, while the corresponding classifier attains 96% accuracy and an AUC of 0.975 in distinguishing weak (M less then 5.5) from strong seismic events. These outcomes underscore the model's capacity to capture complex, nonlinear relationships within catalog-derived features.

Interpretability analyses using feature importance rankings and LIME further reveal that seismologically meaningful variables—such as azimuthal gap, event depth, and RMS error—are the strongest predictors of magnitude and severity. This alignment with established geophysical principles enhances the credibility and utility of the model for domain experts.

It is important to emphasize that this framework is not a forecasting system for future earthquakes. Instead, it serves as a data-driven tool for rapid characterization of seismic events based on metadata available shortly after detection. As such, it holds promise for integration into operational seismic monitoring workflows to support near-real-time situational awareness, early warning triage, and risk-informed decision-making.

5.1 Future Work

To further enhance the framework's applicability, future research will focus on:

Incorporating spatiotemporal sequences and tectonic context (e.g., fault proximity, plate boundary data) to enrich feature representation. Exploring deep learning architectures such as LSTMs, Temporal Convolutional Networks, and Graph Neural Networks to model dynamic seismic patterns. Developing a streaming inference pipeline that interfaces with live USGS or regional seismic feeds for near-real-time event assessment. Expanding explainable AI (XAI) capabilities using SHAP and counterfactual explanations to improve transparency for emergency responders and policymakers. Validating model performance across diverse tectonic regimes (e.g., the Himalayas, Mediterranean, and Andean subduction zones) to assess generalizability and robustness.

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