~ Wisdom Journal For Studies And Research Volume 06 Issue 01/ 28-02-2026

ISSN print/ 2769-1926 ISSN online/ 2769-1934

Artificial Intelligence–Driven Analysis of Seismic Events: Severity Classification and Epicenter Modelling in the Middle East

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Received:17/01/2026 Accepted : 23/02/2026

Abstract:

It proposes a data-driven dual-task framework for seismic event analysis which combines both machine learning and deep learning approaches for classifying the severity level of earthquakes and predicting their epicenter coordinates. The dataset drawn from the Seismological Observatory in Jordan contained geophysical, geographical, as well as temporal features and went through preprocessing involving cleansing of data, normalization, as well as augmentation with synthetic Gaussian noise. These operations enlarged dataset to 10,000 rows and at same time more representative. In addition, earthquakes magnitudes were grouped into low, intermediate and high severity levels. Ensemble models (XGBoost, LightGBM, CatBoost and Gradient Boosting) with model training, performance validation for precision, recall F1 measure & ROC analysis were performed. The models showed high precision and best performance was achieved for Gradient Boosting with 99.67%. Furthermore, for the regression step, stacking ensemble of Multilayer Perceptron, Random Forest and XGBoost were applied for predicting epicenter coordinates. The model was highly predictive with respect to latitude (R^2 = 0.96; MSE = 0.70) and

ISSN print/ 2769-1926 ISSN online/ 2769-1934

the same held for longitude, although it was systematically, but moderately less accurate (R^2 = 0.90; MSE = 4.39). Furthermore, confidence in results was provided through visualizations using residual plots, which also demonstrated practicality and usability of the developed method with interactive maps. It shows that our framework can deal with difficult seismic description and geospatial prediction problems by applying ensemble learning. It provides a basis to concrete the early warning and seismic hazard assessment system in middle east by improving its ability to reach very high intensity class determination and epicentral location approximation.

Keywords: Earthquakes severity classification; Seismic event analysis; Seismic hazard assessment; Ensemble learning; Epicenter prediction; Machine learning.

~ Wisdom Journal For Studies And Research Volume 06 Issue 01/ 28-02-2026

ISSN print/ 2769-1926 ISSN online/ 2769-1934

تحليل الأحداث الزلزالية القائم على الذكاء الاصطناعي: تصنيف شدة الزلازل ونمذجة مراكزها السطحية في منطقة الشرق الأوسط

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ملخص:

تقترح هذه الدراسة إطارًا ثنائيَّ المهمة قائمًا على البيانات لتحليل الأحداث الزلزالية، يجمع بين منهجيات التعلّم الآلي والتعلّم العميق بهدف تصنيف مستوى شدة الزلازل والتنبؤ بإحداثيات المركز السطحي (Epicenter). وقد استندت الدراسة إلى بيانات مستمدة من المرصد الزلزالي في الأردن، تضمنت خصائص جيوفيزيائية وجغرافية وزمنية .وخضعت البيانات لمعالجة مسبقة شملت تنقية البيانات والتطبيع، إضافةً إلى توسيع البيانات عبر إدخال ضوضاء غاوسية اصطناعية، ما أسهم في رفع حجمها إلى 10,000 سجل وجعلها أكثر تمثيلًا للواقع.

كما جرى تصنيف قيم مقدار الزلازل إلى ثلاث فئات للشدة :منخفضة ومتوسطة ومرتفعة .ولأغراض التصنيف، تم توظيف نماذج تجميعية (Ensemble) شملت XGBoost :و LightGBM

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و CatBoostوGradient Boosting، مع إجراء تدريب للنماذج والتحقق من أدائها باستخدام مؤشرات الدقة (Precision) والاستدعاء (Recall) ومقياس F1 وتحليل منحنى .ROC. وقد أظهرت النتائج مستويات دقة مرتفعة، وكان أفضل أداء من نصيب نموذج Gradient Boosting بنسبة بلغت .99.67%

أما في خطوة الانحدار(Regression) ، فقد طُبِّق نموذج تجميع تراكبي (Stacking Ensemble) يضم الشبكة العصبية متعددة الطبقات (MLP) والغابة العشوائية (Random Forest) و XGBoostللتنبؤ بإحداثيات المركز السطحي. وحققت المنظومة قدرة تنبؤية عالية بالنسبة لخط العرض ($R^2 = 0.96$ ؛($MSE = 0.70$ ، وكذلك لخط الطول، وإن كانت دقته أقل بصورة منهجية ولكنها ما تزال جيدة ($R^2 = 0.90$ ؛.($MSE = 4.39$

ولتعزيز موثوقية النتائج، تم تقديم تصورات بيانية باستخدام مخططات البواقي(Residual Plots) ، كما أُبرزت قابلية التطبيق العملي للإطار المقترح عبر خرائط تفاعلية .وتؤكد الدراسة أن هذا الإطار قادر على معالجة تحديات توصيف النشاط الزلزالي والتنبؤ الجغرافي المكاني بكفاءة من خلال التعلّم التجميعي، كما يوفّر أساسًا داعمًا لتطوير أنظمة الإنذار المبكر وتقييم المخاطر الزلزالية في الشرق الأوسط، عبر تحسين القدرة على تحديد فئات الشدة العالية جدًا وتقريب موقع المركز السطحي للزلزال بدقة أكبر.

الكلمات المفتاحية: تصنيف شدة الزلازل، تحليل الأحداث الزلزالية، تقييم المخاطر الزلزالية، التعلم الجماعي، التنبؤ بمركز الزلزال، التعلم الآلي.

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The research

I. Introduction:

Natural calamities like earthquakes affect the physical environment and the social lives of the people. The commencement of an earthquake makes situations catastrophic within minutes. Many lives are lost, and many more lives go unreported. The situation of the injured adds to the burden. The Haiti earthquake is a paradigmatic example of an earthquake. Within minutes of the impact of the Haiti earthquake in 2010, there were 140,000 fatalities. The "golden minutes" of an earthquake are the crucial minutes of an earthquake. This period is crucial for the survival of the people. Earthquakes also displace many people. Many people lose their homes and livelihoods. This leads to the formation of internally displaced persons camps. Earthquakes also bring about regional solidarity. This is exemplified by the Türkiye-Syria earthquake. However, the situation of political tensions makes the situation worse. This is exemplified by the 2023 northwestern Syria earthquake and the 2010 Haiti earthquake. The figures of the people who lost their lives in the 2010 Haiti earthquake are estimates. It is still a challenge to predict earthquakes. This is because of the nonlinear dynamics of the Earth's plates (UNDRR, 2022).

In this context, Artificial Intelligence and Machine Learning technologies have shown great promise in discovering hidden patterns in complex multi-source datasets, providing new opportunities for modern predictive technologies (Reichstein, M., et al. 2019). Ensemble Boosting algorithms have shown great promise as a class of machine learning algorithms that can efficiently deal with complex spatiotemporal classification and regression problems (Rolnick, D., et al. 2022). The research aims to examine the application of four of the best-known boosting algorithms: Gradient Boosting Machines (GBMs), on which the concept of iterative boosting based on gradient descent is derived; XGBoost, or eXtreme Gradient Boosting, which increases the speed and accuracy of predictions through regularization terms; LightGBM, designed to efficiently deal with large datasets through sampling and feature bundling; and CatBoost, which efficiently deals with categorical data and bias reduction through ordered boosting(Bergen et al, 2019).

The aim here is to apply these algorithms to a rich dataset containing a number of seismic parameters, such as historical records of earthquakes, crustal

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deformation data from Interferometric Synthetic Aperture Radar, and a number of geochemical and hydrological parameters (Kong et al, 2019). The aim is to evaluate their ability to predict both the likelihood of an earthquake occurring and its magnitude. While machine learning has shown great promise in seismology, there is a need to evaluate a systematic head-to-head competition between these modern machine learning algorithms in this critical field (Mignan, A., & Broccardo, M.2020). The aim of this research is to lay a foundation to evaluate these algorithms in a precise manner to determine the best algorithm to be used in earthquake prediction (Zhou,. 2012).

II. Literature Review

In recent years, machine learning and deep learning technologies have gained increasing importance in seismic signal analysis, providing effective solutions for event classification, early warning systems, and seismic risk assessment.

The classification of seismic occurrences was examined by Kassa and Dugda (2025) in order to enhance the monitoring of natural earthquakes, non-natural seismic activity, and underground nuclear explosions. The scientists classified occurrences into seven classes using seismic data from the IRIS Data Management Center. These classes included collapses, nuclear explosions, chemical explosions, and various earthquake types. A range of conventional machine learning algorithms were evaluated after careful data processing and feature fitting. Among the tested methods, the random forest model achieved the highest performance, with an accuracy of 93.5%, highlighting its robustness in classifying multi-category seismic events *(Dugda, 2025)*.

Song et al. (2024) was focus of the difference between natural earthquakes and quarry blasts, which is a critical issue for public safety and accurate seismic interpretation. The study used both linear and nonlinear supervised machine learning models to analyze 837 seismic events recorded by the Egyptian National Seismic Network. By incorporating feature selection and explainability tools such as feature importance analysis and SHAP values, the authors demonstrated that only three features—corner frequency, event power, and spectral ratio—were sufficient to achieve high classification accuracy. The XGBoost model outperformed other approaches, achieving a discrimination accuracy of 100% *(Song, J., et al, 2024)*.

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Moving toward deep learning approaches, Chakraborty et al. (2022) proposed the Convolutional Recurrent Model for Earthquake Identification and Magnitude Estimation (CREIME), a multitask framework designed to distinguish seismic signals from background noise, determine the first P-wave arrival time, and estimate earthquake magnitude using raw three-component waveform data from a single station. Despite relying on a short two-second P-wave window, the model achieved an average accuracy of 98% in signal-versus-noise discrimination, along with low errors in arrival time and magnitude estimation, outperforming traditional methods and baseline models *(Chakraborty et al, 2022)*.

Kong et al. (2022) introduced a hybrid seismic discrimination framework that combines deep learning and physical properties to differentiate between earthquakes and explosions. The proposed method integrates waveform-based deep learning representations with physically explainable parameters, such as the ratios of high-frequency primary and secondary wave amplitudes and magnitude differences. This hybrid design showed an improvement in generalization over unseen regions, and an enhancement in interpretability through Grad-CAM visualizations, which helped to address the black-box limitations of deep learning models *(Kong et al, 2022)*.

In the context of earthquake early warning systems, Zhu et al. (2025) addressed the challenge of false alarms caused by microtremors. The authors enhanced a multimodal deep learning network that jointly detects seismic events and classifies earthquake magnitudes. By fusing time-domain and spectral-domain features and training the model on seismic and microtremor signals from the Japanese Kyoshin Network, the proposed approach achieved high recognition rates for microtremors as well as low- and high-magnitude earthquakes, outperforming single-modality models *(Zhu et al, 2025)*.

Beyond event classification, Türkmen and Meral (2024) explored the application of deep learning techniques for single-station epicenter localization using strong motion records. Using the large-scale AFAD-1218 dataset from Turkey, the study demonstrated that deep residual networks and temporal convolutional networks can effectively extract informative features from strong motion data, leading to significant reductions in localization error, particularly when low-quality records are excluded *(Türkmen & Meral , 2024)*.

Earthquake prediction has also benefited from ML-based approaches. Ommi and Hashemi (2024) analyzed seismicity patterns in the north Zagros region

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using Artificial Neural Networks, Random Forest, and Support Vector Machine models to predict significant earthquakes one month in advance. Among the evaluated methods, ANN-based models achieved the best overall performance, suggesting their potential for short-term seismic forecasting and crisis management *(Ommi & Hashemi , 2024).*

Zhexebay (2025) proposed a CNN-based automatic P-wave detection model tailored to the Almaty region, addressing the limitations of traditional STA/LTA and AIC-based techniques under high-noise conditions. Trained on seismic data from multiple stations obtained from the IRIS database, the model achieved an accuracy of 94.1% and demonstrated improved robustness compared to existing deep learning approaches, reinforcing its applicability to early earthquake warning systems *(Zhexebay, 2025)*.

Ertuncay and De Lorenzo (2024) developed a CNN model capable of classifying seismic signals originating from earthquakes, vehicle traffic, and ambient noise. Using accelerometric data collected from stations across Italy, the model achieved over 99% accuracy in multi-class classification and remained reliable even when earthquake signals were superimposed with vehicle-induced noise, highlighting its robustness in real-world environments *(Ertuncay & De Lorenzo , 2024)*.

Lastly, for studying seismicity in a complex tectonic region, Salam and Iqbal (2024) used unsupervised machine learning approaches. Even with minimal data, the study was able to use clustering techniques, specifically Fuzzy C-Means, to identify seismic clusters linked to particular seismogenic structures *(Salam and Iqbal, 2024).* Complementary to this, Vasti and Dev (2025) conducted a comparative evaluation of several deep learning architectures using the STEAD dataset and demonstrated that Long Short-Term Memory (LSTM) networks achieved the highest detection accuracy, outperforming other deep learning models and conventional STA/LTA methods *(Vasti and Dev, 2025)*.

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Study (Author & Year)	Techniques / Models Used	Primary Objective	Key Findings & Performance Metrics
Kassa and Dugda (2025)	Classical ML (Random Forest)	Classification of 7 seismic event types (Nuclear, Chemical, Natural, etc.)	Random Forest achieved the highest accuracy of **93.5%**.
Song et al. (2024)	ML (XGBoost) & Explainability (SHAP)	Discriminating natural earthquakes from quarry blasts	Achieved **100% accuracy** using only three key spectral features.
Chakraborty et al. (2022)	DL (CREIME - CNN-RNN Hybrid)	Signal identification, P-wave arrival, and magnitude estimation	**98% accuracy** in signal-vs-noise discrimination using a 2-second window.
Kong et al. (2022)	Hybrid (DL + Physics-based features)	Differentiating earthquakes from explosions	Improved generalization and interpretability via **Grad-CAM** visualizations.
Zhu et al. (2025)	Multimodal Deep Learning	EEW enhancement and false alarm reduction (microtremors)	High recognition rates for microtremors; outperformed single-modality models.
Türkmen and Meral (2024)	DL (Deep Residual Networks & TCN)	Single-station epicenter localization	Significant reduction in localization error using strong motion records.
Ommi and Hashemi (2024)	ML (ANN, Random Forest, SVM)	Short-term earthquake prediction (one month in advance)	**ANN-based models** showed the best overall performance for forecasting.
Zhexebay (2025)	Deep Learning (CNN)	Automatic P-wave detection in high-noise environments	Achieved **94.1% accuracy**, outperforming traditional STA/LTA methods.
Ertuncay and De Lorenzo (2024)	Deep Learning (CNN)	Classifying earthquakes, vehicle traffic, and ambient noise	Achieved **>99% accuracy** and remained robust under superimposed noise.
Salam and Iqbal (2024)	Unsupervised ML (Fuzzy C-Means)	Seismicity analysis and clustering in complex tectonic regions	Successfully identified clusters associated with specific seismogenic structures.
Vasti and Dev (2025)	Deep Learning (LSTM)	Comparative evaluation of DL architectures using STEAD dataset	**LSTM networks** achieved the highest detection accuracy among all models.

Behind every algorithm mentioned in these studies, and every numerical accuracy achieved, lies the ultimate goal that drives scientific research in this field (protecting human lives and reassuring societies). These research efforts are not merely a display of processing speed or the complexity of mathematical models, but a relentless attempt to understand the silent "pulse of the earth" and transform dry data into an understandable language that

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gives us precious seconds that may be the difference between life and death. Every slight improvement in prediction speed or classification accuracy essentially forms a "digital shield" that protects cities from nature's sudden attacks, embodying humanity's ambition to harness the full potential of its minds to ensure the safety of its kind. The integration of artificial intelligence with Earth sciences sends a reassuring message: technology, in its highest form, is a tool to serve human existence and safeguard its stability in the face of nature's unforeseen challenges.

III. Methodology

In this study, the proposed methodology adopts a data driven scheme, aims to discriminate earthquake intensity and forecast the possible locations of future earthquakes based on hybrid machine learning approaches as well as deep learning algorithms. The data used in this model was obtained from the Jordan Seismological Observatory (JSO) [17] and is considered reliable and accurate for the initial earthquake data. The dataset was constituted by geophysical (depth, magnitude and local name), geographic (latitude and longitude) and time (year, month, day, hour of the day in hours, minutes, seconds). To start with, we clean the data by missing values treatment, removal of corrupted time entries and normalization of all the numeric fields to be consistent float format.

Then, a synthetic data augmentation technique was used to enrich the dataset and alleviate the lack of historical records. This involved generating extra data by adding weighted Gaussian noise to the first order variables: position, depth and magnitude, resulting in a dataset consisting of 10,000 diverse and realistic examples. In order to preserve methodological rigor and avoid possible data leakage, the dataset is logically divided into a training and testing portion first with augmentation only taking place on the training region.

A Datetime property was constructed to feature representative periodic temporal patterns, thus information cyclical temporal features (sin_hour and cos_hour) were extracted in conjunction with the sin_weekday, binary weekend information for better representation of weekday/weekend relevant issues. The names of the locations were converted to numerical codes by using LabelEncoder in order to be compatible with the methods used.

To obtain realistic assessment and avoid overdosed performance, the study chose spatiotemporal holdout splitting strategy. More specifically, a time-based partition was employed (training on earlier records and testing on later

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records) while preserving, as much as possible geographic separation, such that the test set reflect new spatiotemporal conditions. This design better reflects real-world deployment, where models are expected to generalize to future time periods and potentially different spatial clusters. The last split maintained a realistic deployment arrangement by training on an earlier spatiotemporal segment and testing on a later, never-before-seen, segment with similar feature distributions without overlap in location or time clusters. The analysis consists of two main parts in this study. In the first one, earthquake level was classified using magnitude values on a continuous scale converted into three categorical levels: (Low, Medium or High). Manual oversampling for the minority classes, as well as by flexible oversampling techniques such as SMOTE had been used to mitigate issues of class imbalance. The comparison includes four ensemble classifiers: XGBoost, LightGBM, CatBoost and Gradient Boosting with their performance compared by using classification reports, ROC curves and features of eature importance. Hyperparameter optimization was restricted to the training data and performed under a validation regime corresponding to the spatiotemporal split of (e.g., a time-aware validation), where test determination did not play any role for model selection.

Predictive Model for the Epicenter Coordinates The second step involves the development of a regression-based predictive model to predict the epicenter coordinates (latitude and longitude) of future earthquakes. Baseline models such as Multilayer Perceptron (MLP), XGBoost Regressor, and Random Forest Regressor were trained using primary geophysical features and temporal information including magnitude, depth variations, geographic encoding, and time dependent attributes. For better accuracy of predictions, we used a stacking ensemble technique with the base learners as meta-features for a linear regression model. Measured outcomes appear as quantitative values - MSE, R^2, plus location errors in meters. Not just numbers, but signs of how well predictions align with real points on Earth. Geodesic distance, the true path between guessed and actual spots, sets one benchmark. Another view comes from scaling error expressed as a fraction of km, focusing clarity about where actions matter most. This way, distance talks louder than percentages when judging readiness needs across regions. Figure 1 methodology's steps are shown through a flowchart.

This is a framework introduced as a decision-aid for disaster-risk reduction rather than deterministic. The method, by allowing raw seismic records to be

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recast into severity classes and estimated epicenters, may be used to improve initial risk communication, to better guide emergency response and to ensure optimal use of limited disaster resource while saving human lives, and/or reducing material losses, in particularly vulnerable communities. This is even more the case, also in the context of when the "in" in in the context of "this society"), medal east in particular and similar tectonically active regions, where such things as preparedness planning, public awareness and rapid response capabilities are needed if communities are to be resilient.

Finally, the results were visualized into a number of visually appealing plots that showed either true and predicted locations of earthquakes on interactive geographic maps and model's diagnostic performance plots super classifying (the locations) into the model's classification pools. This architecture, which consists of a joint task for earthquake type classification and geographic origin prediction, demonstrated that contemporary, high-performance machine learning techniques can be readily applied to actual seismic risk assessment. Data-based models have started being implemented to enhance the assessment of seismic hazards, and to develop better performing early-warning systems, especially in middle east which share seismotectonic features with e.g. more developed countries.

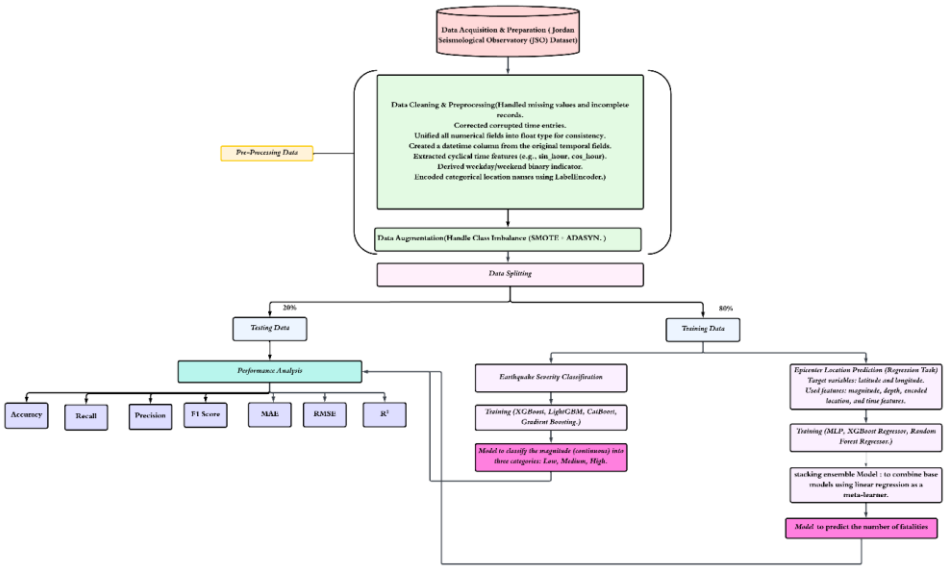


Figure N°1. Flowchart of the Proposed Methodology

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IV. RESULTS AND DISCUSSION

Stage 1: From early findings, patterns emerged when training data sorted earthquake severity into low, medium, or high tiers. Four (XGBoost, LightGBM, GradientBoost and CatBoost) chained execution of ensemble-based classifiers the four main performance measures—accuracy, recall, precision and F1 score—were extracted from confusion matrices. In this paper, these measures are used to measure the classification performance. Table 1 shows the results.

Table N°1. Earthquake Severity Classification Results Based on Training Ensemble Classifier Algorithms

Model Name	Earthquake Severity Class	Metrics			
		Precision	Recall	F-Score	Accuracy
XGBOOST	2	1.00	1.00	1.00	
	0	1.00	0.95	0.98	0.9843
	1	0.96	1.00	0.98	
LightGBM	2	1.00	1.00	1.00	
	0	1.00	0.99	0.99	0.9941
	1	0.9	1.00	0.99	
CatBoost	2	1.00	1.00	1.00	
	0	1.00	0.98	0.99	0.9921
	1	0.98	1.00	0.99	
GradientBoosting	2	1.00	1.00	1.00	
	0	1.00	0.99	1.00	0.9967
	1	0.99	1.00	1.00	

Figure 2: Correlation Matrix The above plot is an important quantitative summary in terms of linear relationships among features in a dataset. Next in form of heatmap of the Pearson correlation coefficients, it indicates that the Magnitude of the earthquake varies in a non-straining manner with most of the attributes that were considered. It has almost no or very low association with space and time and a closer examination shows it only weakly positively is correlated with Depth (0.13). This is important for validating that the

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seismic mechanism of action is complex non-linear behavior and was therefore necessary when designing our modeling strategy. This in turn, is a compelling motivation for justifying our use of advanced ensemble learning methods based on boosting: XGBoost and CatBoost – both of them highly capable to capture complex patterns, thus allowing to build powerful classification and prediction frameworks.

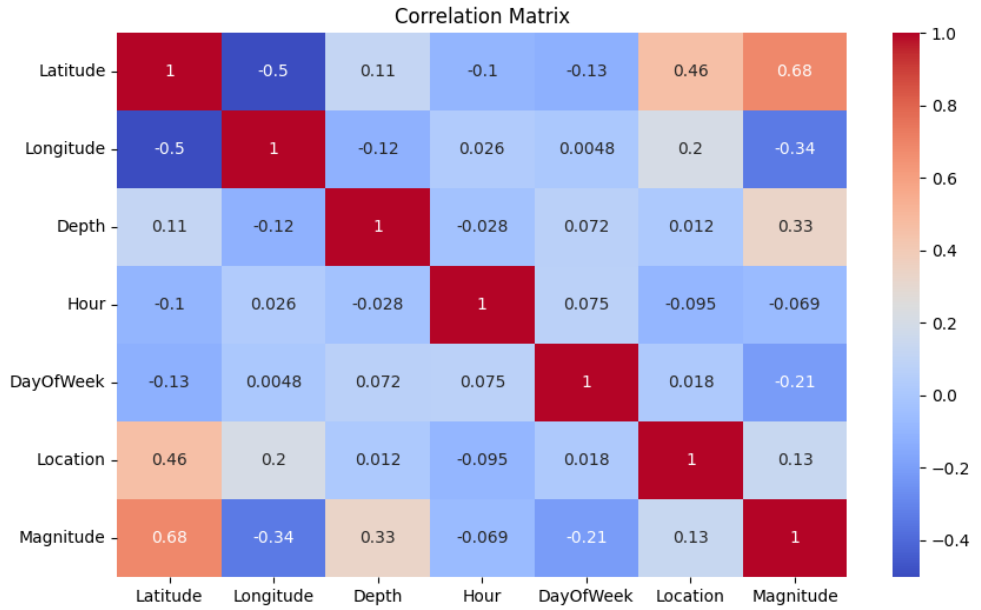


Figure N°2. Correlation Matrix of the Dataset Features

Figure 3 shows the ROC curves of the four ensemble-based classifiers that we used to classify our earthquake severities. The highlight of the figure is that curves for all the models collapse around the top-left corner, which shows that they have a great discriminatory power here. However, the category accuracy was not uniform across categories upon closer examination. The curves for high and moderate intensity nearly overlaid on small axes, indicating a near perfect classification accuracy, but at low intensity, slight deviation from this ideal point represented the highest and lowest repeatability. Indeed, this close-up visual inspection supports the higher accuracy and recall values shown in our tables and reflects on the effectiveness and resilience of our seismic event classification method. high-quality severity classification is important because it can tag alerts and response levels (e.g., rapid inspection of infrastructure, hospital preparedness,

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public-safety messaging) in the order of the anticipated intensity category so that casualties are minimized and cascading socio-economic impact ameliorated.

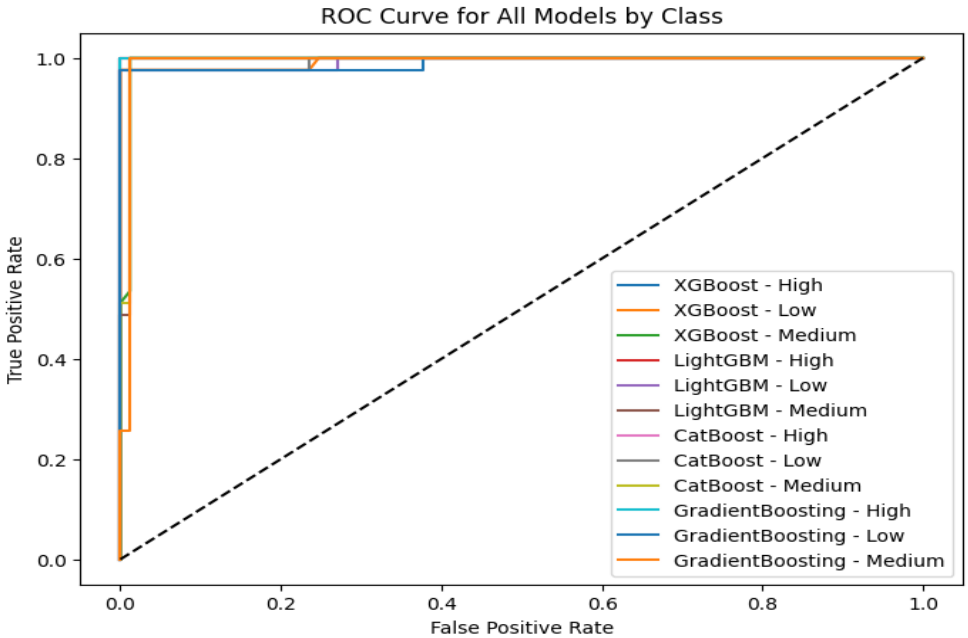


Figure N°3. Receiver Operating Characteristic (ROC) Curves for Earthquake Severity Classification Models.

Figure 4 shows a comparison among the four ensemble classifiers based on their performance in discriminating between three predefined earthquake severity levels. This bar chart displays the impressive results of all our models by looking at our summary table shown graphically. It is interesting to observe that GradientBoosting has the highest accuracy of 99.67% and it almost catches up with LightGBM and CatBoost. Though it achieves an accuracy of 98.43%, slightly lower than the best, it still demonstrates robust and efficient classification performance. The performance differences were marginal, yet all models performed above 98% accuracy, which supports the robustness of our feature selection and data preprocessing steps.

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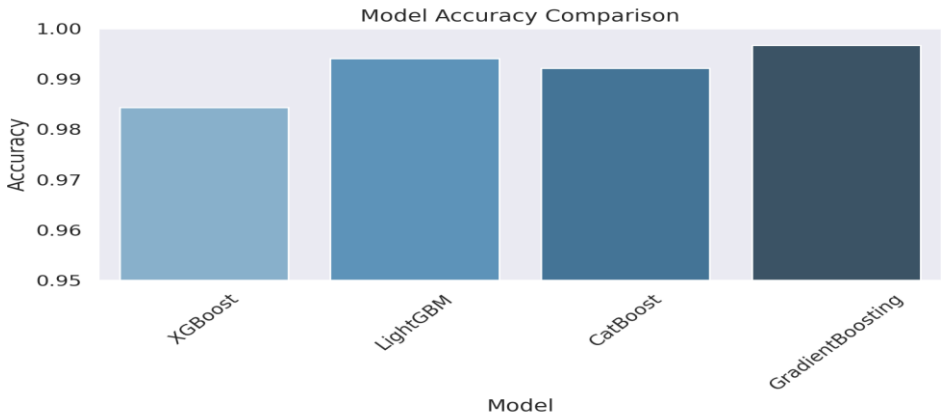


Figure N°4. Comparative Accuracy of Ensemble-Based Classifiers for Earthquake Severity Classification

In the second stage, a regression model was constructed to predict the earthquake epicenter (in degree of longitude and latitude). Applied algorithms were MLP, RF and XGBoost. By stacking the previous algorithms you were able to harness some single best characteristics of both algorithms, but this required an occasionally more complex technique than by using linear regression to combine the predictions (outputs) of such a models; to be used as descriptive features for our final linear regression model where performance was evaluated using: mean squared error (MSE), R-squared (R^2). Table 2 shows the results.

Table N°2. Regression Performance Metrics for Earthquake Epicenter Coordinate Prediction

Metric	Latitude Prediction	Longitude Prediction
Mean Squared Error (MSE)	0.7051	4.3928
R-squared (R^2)	0.9627	0.9015

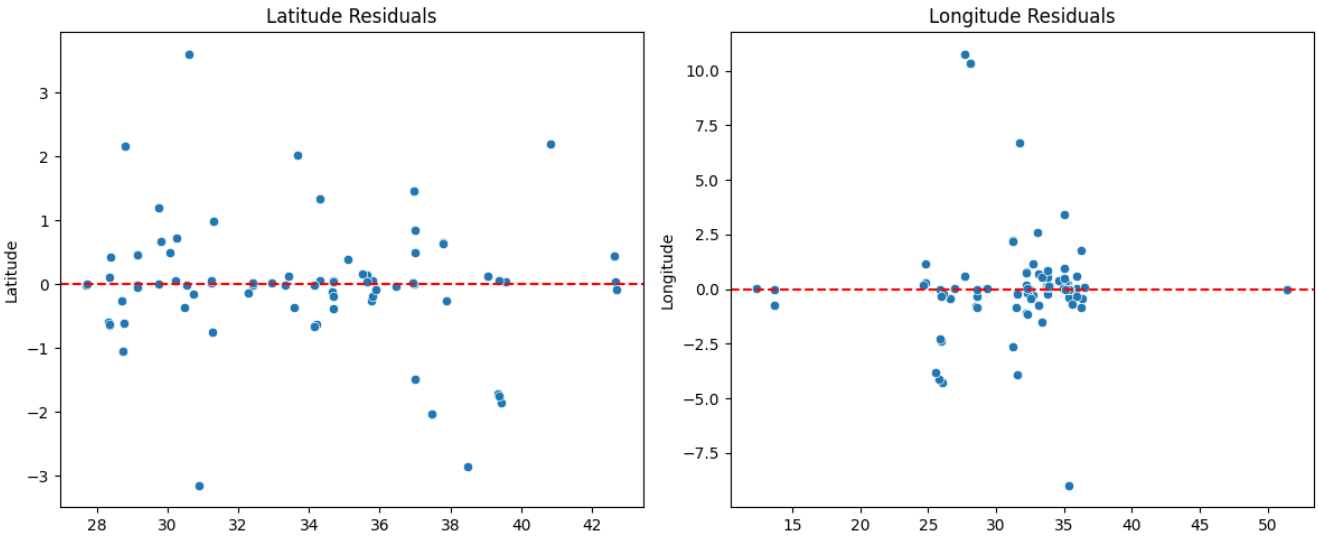
As shown in Table 2, the ensemble model performed well for prediction and got strong results (an R^2 of 0.96 and an MSE of 0.70) especially for predicting latitude of earthquake epicenters, for which it provided a highly reliable estimation. The longitude prediction was not quite as accurate, but the interpretability and generalizability of the model remained high. The results presented here demonstrate and confirm the importance of ensemble

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learning methods (stacking ensemble model in our study) for complex geospatial regression problems. Hence this technique will be successful in predicting the coordinates of an earthquake location.

Figure N°5. Residual Plot for Earthquake Epicenter Coordinat Prediction Model

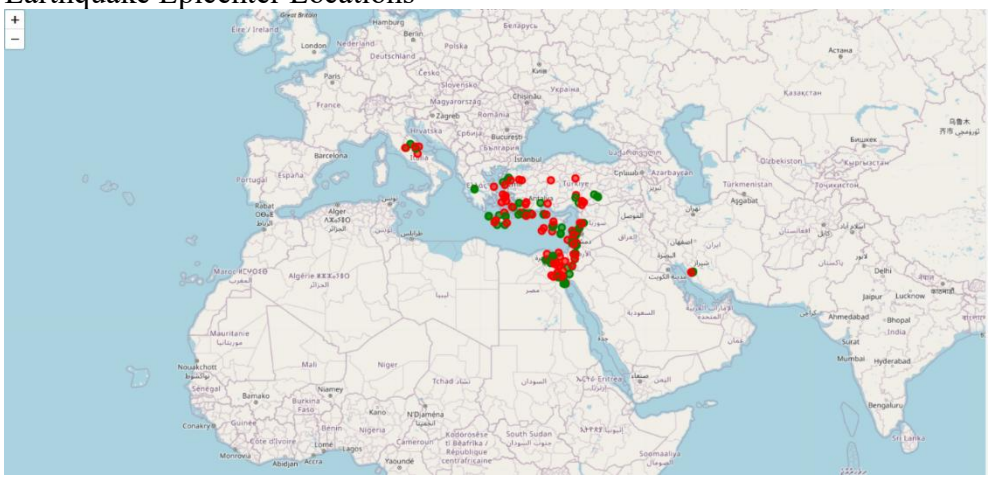
Residual plot is one of the key diagnostic plots, it helps the evaluator in



drilling down to the details of how well our regression model has performed to predict earthquake epicenter coordinates, as shown in figure 5. The subplot of latitude residuals offers a confined random scattering of these points centered upon the zero line, a marker for stable model, which correlates well with the significant statistical results along these lines ($R^2 = 0.96$ and MSE = 0.70, Table 2). The longitude residual plot is similarly showing a good performance, that is, most of the points are situated near the zero line, but it still has a little wider spread and some major outliers. This marginal difference in precision of both predictions is demonstrated by the slightly lower R^2 (.90) but higher MSE (4.39) for longitude, giving a strong and complimentary visual validation of the strengths and weaknesses of our model for this complicated geospatial problem.

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Figure N°6. Interactive Geographic Map of Actual and Predicted Earthquake Epicenter Locations



Source: Prepared by the authors (2025)

On the location of earthquake epicenters, Figure 6 is an excellent visual tool for demonstrating some intuition about capability of model to make predictions. The map is equipped with the double-marker system: green circles are true epicenters from dataset; red circles are coordinates predicted by our stacking ensemble model. At the first glance (the ball of red points is close to that of green) we see in pictures that our model makes quite few errors. It is actually this narrow clustering which directly supports the numerical results in Table 2. small MSE and high R-squared for both latitude and longitude. The map has the salutary property of tying statistical quantities to real-world applications, and it reveals just how well the model succeeds at predicting future earthquakes, and doing so with enough lead that it can be put on a scale that will matter for better early-warning systems.

In an operational context, we might use a good estimate of the epicenter to establish early situational awareness for civil defense and local authorities , where to send search-and-rescue teams; how to route emergency services; what areas likely have damage that needs efficient triage. Such decision support will proactively avoid unnecessary loss of life, human resources, and materials; and enhance community resilience. Importantly, it is important not to treat predictions as truth or absolute but rather probabilistic advice and supplement official seismic monitoring/ expert advice. While the models work well, earthquake processes are inherently complex and influenced by

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unobserved geophysical states as well as lack of data. So, the results are to be viewed as a probabilistic diagnostic aid that can help official monitoring and experts' evaluation, but not as deterministic prediction. This approach is intended to improve response and preparedness planning, risk communication, resource allocation, and community resilience.

In summary, findings in this work provide evidence in favor of our task-free, data adaptive approach for assessing seismic events. All these ensemble-based classifiers performed well in classification, particularly Gradientboosting model with an excellent accuracy of 99.67% in classifying the intensity level of earthquake during the classification phase. This strong finding is also visually confirmed by the closely stacked ROC curves, which are indicative of superior discriminatory ability of models. For the regression task, an ad-hoc prediction of longitude and latitude coordinates (which is a highly sensitive measure) was performed with high accuracy: $R^2 > 0.96$ & low MSE < 0.70 for latitudinal prediction). Although predictions of longitude are not as accurate, the larger residual scatter and R^2 statistic (0.90) indicates that model performance has not been degraded. In general, the integration of these innovative machine learning tools proved to be an efficient tool for addressing complex spatial and classification problems with promising future developments on the comprehension seismic risk and in deploying more efficient early warning system systems in seismically active regions.

These results appear to be very compatible with the outputs of this study and can (probabilistically) attest to that AI-informed analytics can construct a "decision-support infrastructure enhance disaster preparedness". By improving severity classification and estimating likely locations, the approach could enable policy makers, local governments and emergency responders to take faster, more informed actions that can save lives while reducing displacement and economic cost of earthquakes on households and services.

CONCLUSION

This study proposes an AI-driven dual-task framework for seismic event analysis in the Middle East, integrating earthquake severity classification and epicenter coordinate modelling within a unified, data-driven pipeline. Using a reliable earthquake catalog from the Jordan Seismological Observatory, the study applied rigorous preprocessing, feature engineering, and controlled synthetic augmentation to improve data quality and learning stability. A

ISSN print/ 2769-1926 ISSN online/ 2769-1934

spatiotemporal holdout strategy was adopted to better approximate real deployment conditions by testing on later and spatially distinct segments rather than randomly mixed samples. Results demonstrate that ensemble learning delivers strong performance across both tasks. For severity classification, all boosting-based models achieved accuracies above 98%, with Gradient Boosting providing the best overall accuracy (99.67%), supporting its use as a rapid screening layer for intensity-based prioritization. For epicenter prediction, a stacking ensemble (MLP, Random Forest, and XGBoost with a linear meta-learner) achieved high predictive capability for latitude ($R^2 = 0.96$; MSE = 0.70) and robust performance for longitude ($R^2 = 0.90$; MSE = 4.39). Residual diagnostics and interactive spatial visualizations further confirmed close alignment between predicted and observed locations, reinforcing practical applicability. Beyond technical contributions, this work emphasizes societal value: AI-based analytics can support disaster-risk reduction by enhancing preparedness, improving responsiveness, and informing resource allocation and risk communication, thereby helping reduce preventable casualties and material losses, especially in high-exposure communities. Importantly, outputs should be interpreted as probabilistic decision support rather than deterministic prediction and used alongside official monitoring and expert judgment. Future work should expand regional datasets, incorporate additional geophysical signals, report distance-based geographic error more explicitly, and integrate uncertainty estimation to strengthen operational reliability.

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