Journal of Intelligent Systems and Internet of Things
Vol. 18, No. 02, PP. 386-409, 2026
DOI: https://doi.org/10.54216/JISIoT.180227

Optimizing Earthquake Prediction Accuracy using Somersaulting Spider Optimizer for Dynamic Ensemble Weighting

Ahmed Mohamed Zaki[1,*], Hala B. Nafea[1], Hossam El-Din Moustafa[1,2], El-Sayed M. El-Kenawy[3,4,*]

[1]Department of Electronics and Communications Engineering, Faculty of Engineering, Mansoura University, Mansoura, 35516, Egypt

[2]Faculty of Artificial Intelligence and Informatics, Horus University, New Damietta, 34517, Egypt

[3]Department of Communications and Electronics, Delta Higher Institute of Engineering and Technology, Mansoura, 35111, Egypt

[4]Applied Science Research Center, Applied Science Private University, Amman, Jordan

Emails: ahmeduzaki@std.mans.edu.eg; halabahyeldeen@mans.edu.eg; hossam_moustafa@mans.edu.eg; skenawy@ieee.org

Abstract

Earthquake prediction is one of the most challenging problems in geophysical science, and conventional approaches have proven arduous in capturing the complexity and non-linearity of seismic measurements. The multidimensional nature of earthquake variability, along with class imbalance and the strong dependence of prediction results on hyperparameters, necessitates the development of more robust and flexible predictive models. In this paper, we introduce a bio-inspired ensemble learning method based on the Somersaulting Spider Optimizer (SSO) for dynamically adjusting classifier weights in earthquake classification. The proposed method addresses limitations of existing weighting strategies, which primarily focus on maximizing classifier contribution based on performance characteristics. Experiments were conducted on an earthquake dataset augmented with features modeled and mapped by time, space, and magnitude to capture patterns of seismic events. We compared the SSO-optimized ensemble with BaggingClassifier, CatBoost, HistGradientBoosting, LightGBM, and DecisionTree, as well as traditional ensemble approaches. Results show that the SSO-boosted ensemble achieved superior performance, with an accuracy of 97.01%, sensitivity of 97.04%, specificity of 99.36%, precision of 97.64%, and an F1-score of 97.33%, outperforming other models and traditional ensembles. These improvements were confirmed statistically using Wilcoxon signed-rank tests, while visual analyses demonstrated enhanced stability and generalization. Overall, the integration of bio-inspired optimization and ensemble learning shows strong potential to overcome challenges in earthquake forecasting and to support reliable early warning and disaster preparedness systems.

Received: June 5, 2025 Revised: July 28, 2025 Accepted: September 10, 2025

Keywords: Earthquake prediction; Ensemble learning; Somersaulting spider optimizer; Bio-inspired optimization; Seismic classification; Machine learning

1 Introduction

Earthquakes are one of the most devastating natural hazards, posing a significant threat to human security, infrastructure stability, and economic sustainability at the global level [1]. Because of the inherent unpredictability of seismic events and the complexity of the underlying geological processes associated with them, there has been continual scientific effort to develop consistent forecasting and classification methodologies. Recent advancements in data science [2], earthquake monitoring technologies, and a deeper understanding of seismogenesis have significantly enhanced the development of computational methods for earthquake prediction. Over the past few decades, these interdisciplinary innovations have facilitated the integration of vast and complex datasets, improved the accuracy and sensitivity of real-time monitoring systems, and fostered the creation of more robust models for forecasting seismic events. As a result, contemporary earthquake prediction frameworks now benefit from the synergy of sophisticated machine learning algorithms, high-resolution sensor networks, and an enriched theoretical foundation regarding the mechanisms underlying seismicity. These developments collectively represent a substantial leap forward in our ability to anticipate and mitigate the impact of earthquakes [3], [4].

Traditional seismic instrumentation has mainly used physical sensor networks and empirical ground motion models [5]. Many of those conventional methods, nevertheless, have not been able to capture the nonlinear relationships inherent in seismic data. The limitations are most pronounced with different datasets with spatial variations or temporal variations. To overcome these limitations, machine learning and deep learning techniques have been recently gaining more popularity as seismological research methods, and appear to have great potential to extract the small-scale patterns in high-dimensional seismic signals [6]. In addition, satellite remote sensing has also expanded the potential of monitoring and analyzing seismic precursors over large spatial scales thanks to its integration with other technologies [7].

Earthquake prediction poses another important and challenging problem due to the nonlinear and heterogeneous nature (regional), coupled with the incompleteness of seismic systems. Empirical relationship models and physical simulation models contribute valuable information, but are not suitable for resolving high-dimensional, uncertain and time-varying seismic data [8]. Recent developments in computational seismology have brought up the topic of using data-driven methods based on machine learning, deep learning or hybrid optimization algorithms [9]. These methods have shown promise for identifying latent patterns, detecting precursor signals, and improving short- to medium-term forecasting accuracy. Specifically, the introduction of ensemble structures has enabled better decision-making by incorporating multiple models, mitigating overfitting, and enhancing generalization to new seismic conditions.

The interdisciplinary nature of earthquake impacts can also be observed from the scientific response to recent large-scale seismic events involving not only geophysical modeling but also infrastructure resilience, social media analytics, and emergency response systems in earthquake impact prevention and management scenarios [10]. Furthermore, the development of remote sensing and distributed sensing technologies, as well as self-supervised learning frameworks, has addressed several deficiencies in sparse labeling and real-time monitoring requirements [11]–[14].

The use of various geophysical predictors including environmental, satellite-based, and anthropogenic variables has led to the advancement of forecasting studies in new directions [15]. The trends point towards a clear need to adopt scalable and adaptive, interpretable models that can integrate heterogeneous data sources effectively. Following these developments, this study proposes a more streamlined ensemble classification framework inspired by the Somersaulting Spider Optimizer (SSO), in an attempt to enhance accuracy, reliability, and the versatility of earthquake prediction systems.

However, there are still issues with hyperparameter sensitivity, class imbalance, and overfitting, particularly with rare but significant events, despite advances in earthquake forecasting. This research attempts to overcome these drawbacks by proposing an adaptive ensemble learning model that employs the Somersaulting Spider Optimizer (SSO), a bio-inspired metaheuristic that dynamically sets the weights of the classifiers automatically to achieve improved performance in terms of accuracy and robustness. Evaluated on a comprehensive Los Angeles earthquake dataset with designed temporal, spatial, and magnitude-based features, the SSO-enhanced ensemble demonstrates better generalization and stability than individual models through statistical and visual measures.

The key contributions of this work are summarized as follows:

- **Novel Bio-Inspired Ensemble Optimization:** This study introduces the first application of the Somersaulting Spider Optimizer (SSO) for dynamically adjusting ensemble weights in earthquake prediction, enabling adaptive classifier contributions that outperform static weighting schemes.

- **Robust Real-World Validation:** The proposed method is evaluated on a high-quality, real-world earthquake dataset from Los Angeles, incorporating engineered variables to reflect realistic seismic patterns and forecasting conditions.

- **Extensive Comparative Benchmarking:** Performance is benchmarked against multiple state-of-the-art classifiers (e.g., BaggingClassifier, CatBoost, HistGradientBoosting, LightGBM, DecisionTree) and traditional ensemble approaches, highlighting the superiority of the SSO-optimized ensemble.

- **Comprehensive Performance Evaluation:** A multi-metric evaluation framework is implemented, including accuracy, sensitivity, specificity, precision, NPV, and F1-score, alongside statistical validation (Wilcoxon signed-rank test) and performance visualizations.

- **Reproducible Methodology:** Detailed procedural descriptions, statistical tests, and result visualizations are provided to ensure reproducibility and facilitate further research in seismic classification.

The remainder of this paper is organized as follows: Literature Review surveys related research; Materials and Methods details the dataset, ensemble learning, and the Somersaulting Spider Optimizer; Experimental Results reports baseline and SSO-optimized performance with statistical validation; Conclusion and Future Work summarizes the findings and outlines future directions; these are followed by Data Availability and Declarations.

2 Literature Review

There is a growing trend towards the utilisation of deep learning methods in seismic waveform analysis, enhancing earthquake surveillance. According to the results of [16], a data recombination technique can be used to create synthetic earthquake data that can be applied in different locations and station combinations to train neural networks. This methodology allows the creation of models that can be used universally in a wide range of monitoring systems to detect earthquakes and estimate earthquake parameters using continuous seismic signals, thereby allowing Earthquake Early Warning (EEW) to be activated quickly.

A sophisticated machine learning approach can be used to improve earthquake prediction in Los Angeles, California. According to [17], the maximum potential magnitude of an earthquake can be predicted by using a specially designed feature matrix, and the predictions are made by synthesizing existing studies with new predictive features, which is why the Random Forest model outperforms other machine learning models in making predictions in the maximum earthquake category within a 30-day time frame.

The timely and precise forecasting of the maximum acceleration of the ground (PGA) has been an important cornerstone of earthquake early warning (EEW) systems on the ground. In [18], an end-to-end deep learning model DLPGA was introduced to predict PGA using convolutional neural networks (CNNs) to avoid restrictions related to the use of traditional feature parameter selection. This model uses vertical initial-arrival 3–6-second seismic waves recorded at a single station as input and automatically computes features using a multilayer CNN, allowing prediction of PGA quickly; the results showed that DLPGA is more effective in on-site EEW testing ground motion destructiveness than methods based on artificially defined feature parameters.

Strain monitoring by boreholes is critical in the development of precursor studies of earthquakes. Following [19], a new technique that could be used to overcome the disadvantages of the classical method in working with large volumes of data in borehole strain monitoring was created; this method involves segmented variational mode decomposition along with a GRU-LUBE deep learning network that will increase data correlation during the decomposition process and enable successful prediction of borehole strain variations.

The problem of predicting failure in solids is an important one with significant applications in other spheres, such as the elusive endeavor of earthquake prediction. According to the results cited in the literature review of the paper [20], Physics-Informed Neural Networks (PINNs) provide a promising way to approach machine learning-based failure prediction by including fault physics in the deep learning loss function and using time-lapse ultrasonic measurements to achieve better scalability and transfer learning.

Earthquakes pose a substantial risk to human life, residential areas, and critical infrastructure. According to the analysis by [21], deep learning models, particularly those employing graph convolutional neural networks with batch normalization and attention mechanisms, offer a promising avenue for earthquake prediction by estimating event depth and magnitude using seismic station data. Leveraging waveform data preprocessing and feature extraction with convolutional neural networks, these models utilize attention mechanisms to prioritize salient features and batch normalization to enhance training stability and speed; ultimately, integrating these elements with event location information enables accurate prediction of event parameters.

Machine learning techniques are gaining traction within seismology and earthquake science. As demonstrated by [22], lab-based investigations leverage acoustic emission data to forecast time-to-failure and stress conditions, with limited applications extended to field data. It has been shown that elastic waves passing through the lab fault zone contain information that can predict the full spectrum of labquakes from slow slip instabilities to highly aperiodic events.

Prior investigations have demonstrated a notable correlation between local and regional seismic events and the emission of radon gas from the soil. As evidenced in the study by [23], radon measurements can be effectively utilized to estimate seismic activity rates, offering a novel approach to earthquake forecasting by analyzing radon time series data and identifying characteristic precursors at different time scales, ultimately serving as a valuable complement to conventional seismic analysis techniques.

Earthquake statistics provide crucial probabilistic insights, and advancements in high-precision observation technologies and machine learning are collectively improving our understanding of intricate earthquake behaviors. As outlined in the research of [24], individual large earthquakes may possess unique signatures representable through novel high-dimensional features like Gauss curvature-based coordinates, where earthquake catalog data is converted into pseudo physics quantities (energy, power, vorticity, and Laplacian) and transformed into smooth surface-like information via spatio-temporal convolution, ultimately suggesting the feasibility of data-driven prediction models customized for individual large seismic events.

Earthquakes pose a significant threat to human life and infrastructure. As reported by [25], artificial intelligence methods have been employed in attempts to predict these events; however, achieving high accuracy has been challenging because of the complexities inherent in large, multidimensional datasets and limitations related to data handling. Drawing from the work of [25], federated learning (FL) emerges as a promising machine learning approach for earthquake prediction, offering a way to analyze data locally while preserving data privacy and minimizing the need to transmit sensitive information to a central server.

Earthquakes represent a major natural hazard, contributing significantly to global mortality over the past half-century. In the analysis provided by [26], a novel machine learning method, Inverse Boosting Pruning Trees (IBPT), is developed to forecast short-term earthquakes using satellite data from 1371 earthquakes of magnitude six or greater, recognizing their substantial environmental impact. This framework's performance was evaluated against six state-of-the-art machine learning methods, leveraging ten distinct infrared and hyperspectral measurements gathered between 2006 and 2013, showcasing improved earthquake forecasting accuracy across various earthquake databases.

The persistent challenge of earthquake prediction remains a significant hurdle in Earth science. [27] Google's Machine Learning competition platform, Kaggle, engaged the global Machine Learning community to enhance data analysis methods for forecasting, specifically using laboratory earthquake data. The competition involved predicting the time remaining before subsequent laboratory earthquakes based on limited seismic data. More than 4,500 teams developed and shared over 400 computer programs, using unexpected strategies like rescaling failure times and comparing input distribution of training and testing data, alongside established seismic data features mapping fault criticality. The competition also served as a tool for teaching Machine Learning in geophysics, potentially offering a model for engaging the Machine Learning community on other geoscientific problems.

Machine learning techniques have demonstrated the ability to forecast the occurrence and intensity of laboratory-induced earthquakes by analyzing acoustic emission statistics. Based on the findings of [28], the amount of acoustic energy released during lab experiments is directly related to fault slip rate when using larger grains (10.5 m); specifically, minimal acoustic energy is observed when the fault is immobile, escalating to a peak during coseismic rupture, highlighting a strong correlation between acoustic emissions and frictional contact mechanics as well as time-dependent fault healing processes.

Earthquake prediction remains a significant, yet difficult undertaking in the earth sciences, complicated by inherent uncertainty, necessitating probabilistic approaches. In the view of [29], the application of machine learning methods to large-scale images, videos, and text processing has seen significant advancements, but their adoption in earthquake probability assessment has been limited. Using convolutional neural networks, a deep learning technique, to generate scalable earthquake probability mapping has been proposed [29].

Machine learning techniques have been applied to data from the LANL earthquake prediction competition on Kaggle to develop models for predicting earthquakes. In the research conducted by [30], machine learning was leveraged to build predictive models using data derived from a laboratory stick-slip friction experiment, mirroring actual seismic events, where digitized acoustic signals were documented against the time leading up to the failure of a granular layer compressed between steel plates. The study underscores the potential of machine learning in seismology by demonstrating that an optimal set of statistical features describing acoustic data can effectively predict the time remaining until failure.

Understanding the factors that govern earthquake distribution and magnitude is crucial for improving earthquake forecasting capabilities. Following the work of [31], a study of Italian seismicity reveals a correlation between the rate of crustal movement and earthquake characteristics. The research, which leverages a high-resolution horizontal strain rate field derived from two decades of GNSS and satellite radar interferometry data, statistically analyzes the relationship between strain rate (S) and the magnitude of earthquakes ($M \geq 2.5$) observed during the same period. The findings indicate a linear relationship between S and earthquake probability, suggesting that a doubling of S corresponds to a doubling of the likelihood of a significant seismic event; furthermore, lower strain rate zones, while less probable, can still experience earthquakes of comparable magnitude to those in high strain rate zones. This work provides an independent and quantitative method for spatially forecasting seismicity.

Table 1 provides a comparative analysis of various research approaches within earthquake studies, specifically focusing on earthquake prediction, earthquake forecasting, and earthquake early warning. It explores the application of machine learning and deep learning techniques using seismic precursors, GNSS data, and radon emissions, among other methods. The table below summarizes their main focus, methodology, and key findings.

Table 1: Comparison of Machine Learning (ML) and Deep Learning (DL) Methods for Earthquake Prediction and Forecasting.

No.	Main Focus	Methodology	Key Findings
Ref [16]	Real-time earthquake early warning using generalized earthquakes.	Deep learning with data recombination to create generalized earthquakes for training.	Improved generalization of EEW neural networks to diverse regions.
Ref [17]	Improving earthquake prediction accuracy in Los Angeles.	Machine learning and neural networks with comprehensive feature matrix.	Robust model for estimating maximum potential earthquake magnitude.
Ref [18]	Peak ground acceleration prediction for on-site EEW.	Deep learning for PGA prediction using P-wave parameters.	Improved accuracy and timeliness of PGA prediction in EEW systems.
Ref [19]	Pre-earthquake anomaly extraction from borehole strain data.	Segmented VMD and GRU-LUBE deep learning network.	Enhanced data correlation during decomposition for anomaly detection.
Ref [20]	Predicting lab earthquakes using physics-informed neural networks and acoustic monitoring.	Physics-informed neural network trained with fault zone acoustic data.	Lab earthquakes can be predicted using micro-failure events and fault zone elastic properties.
Ref [21]	Early warning system for earthquake prediction from seismic data.	Batch Normalized Graph Convolutional Neural Network with Attention Mechanism.	Deep learning model for predicting earthquakes, providing location, magnitude, and depth.
Ref [22]	Predicting timing and shear stress of lab earthquakes.	Machine learning using active seismic monitoring of fault zone processes.	Lab earthquake prediction and seismic forecasting through acoustic emission data.
Ref [23]	Relationship between radon measurements and seismic activity rate in Vrancea.	Analysis of radon measurements in relation to daily seismic activity rates.	Methodology to estimate seismic activity rate using radon measurements.
Ref [24]	Data-driven prediction using Gauss curvature signatures of large earthquakes.	Identification of unique Gauss curvature signatures for individual earthquakes.	Customized data-driven prediction of individual large earthquakes' locations and magnitudes.
Ref [25]	Earthquake prediction using federated learning.	Federated learning framework for distributed seismic data analysis.	Addresses data privacy and computational challenges in earthquake prediction.
Ref [26]	Advancing earthquake forecasting using machine learning of satellite data.	Machine learning analysis of satellite-derived data.	Exploration of satellite data for improving earthquake forecasting reliability.
Ref [27]	Laboratory earthquake forecasting through machine learning competition.	Machine learning algorithms applied to lab earthquake data.	Crowdsourcing data analysis approaches for improved forecasting.
Ref [28]	Acoustic energy release during laboratory seismic cycle.	Machine learning and acoustic emission analysis.	Connections between acoustic energy and fault zone processes leading to failure.
Ref [29]	Earthquake probability assessment for the Indian Subcontinent.	Deep learning for earthquake probability assessment.	Scalable probability assessment models for seismic data.
Ref [30]	Machine learning modelling using data from seismology experiment.	Machine learning modeling using LANL earthquake prediction competition data.	Application of machine learning to lab-based stick-slip friction experiment.

Continued on next page

Table 1 – *Continued from previous page*

No.	Main Focus	Methodology	Key Findings
Ref [31]	Spatial forecasting of seismicity using Earth observation.	Correlation analysis between earthquake distribution and crustal movement.	Relationship between strain rate and the distribution/size of earthquakes.

In summary, the reviewed literature reveals a collective effort towards improving earthquake understanding and mitigation, with studies exploring a range of strategies including earthquake prediction, forecasting, and early warning systems. The approaches are diverse, encompassing machine learning and deep learning algorithms applied to seismic precursors, GNSS data, and radon emissions. Current trends suggest a growing integration of multi-disciplinary data and increasingly sophisticated computational methods; future research should focus on developing robust, real-time systems that can effectively translate scientific advancements into actionable alerts for vulnerable populations.

3 Materials and Methods

This section outlines the methodology employed in this study, encompassing the dataset characteristics, ensemble learning design, and the optimization strategy developed to enhance classification performance for earthquake forecasting. The approach integrates advanced machine learning algorithms with bio-inspired optimization to construct a robust and adaptive prediction framework. First, the Los Angeles Earthquake Dataset is analyzed to extract meaningful features that reflect both spatial and temporal seismic dynamics. Next, an ensemble learning strategy is implemented to leverage the complementary strengths of multiple base classifiers. Finally, the Somersaulting Spider Optimizer (SSO) is applied to optimize ensemble weight coefficients, ensuring balanced contributions from all models and achieving superior generalization performance.

3.1 Dataset

The Los Angeles Earthquake Dataset consists of 22,899 seismic events and 20 features describing the location, magnitude, time dynamics, and statistical measurements of seismicity of events [32]. It covers both fundamental parameters (latitude, longitude, magnitude) and provides information on earthquake scaling laws and spatial–temporal clustering. Other features such as elapsed time, maximum magnitude during the past week, and the number of such events more than 30 days in the past are useful in terms of time for understanding aftershock patterns and seismic hazard. There is also a classification label in the dataset which can be used with machine learning to categorize and predict seismic events.

The class column in this dataset is a categorical classification of earthquake magnitudes which has six distinct classes. Every class is associated with a certain magnitude range; smaller classes are referred to as weaker earthquakes, and higher classes have stronger seismic activity potential, which allows a structured risk estimation and forecasting. The dataset can be accessed publicly here: `https://doi.org/10.5281/zenodo.13738725`.

Figure 1 depicts the magnitude distribution histogram of the Los Angeles earthquake dataset, illustrating the frequency of seismic events across various magnitude classes, which provides foundational insights into the scale and intensity of recorded earthquakes.

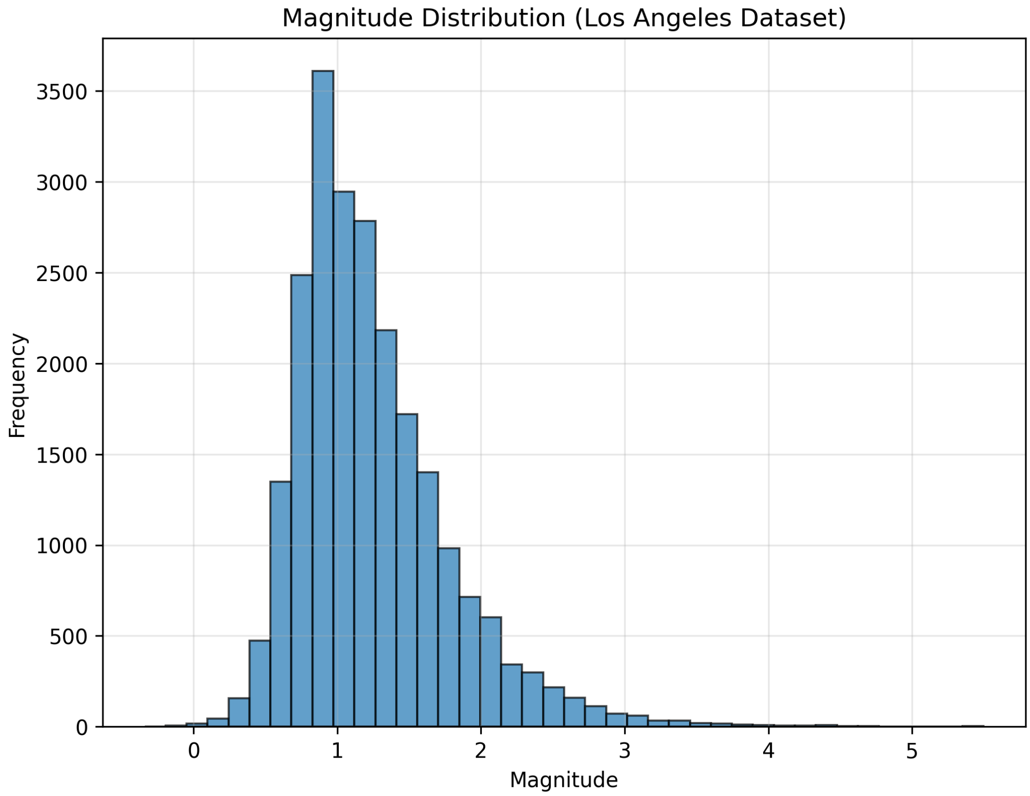

Figure 1: Histogram Showing the Frequency Distribution of Earthquake Magnitudes in Los Angeles.

Figure 2 presents a spatial scatter plot mapping the geographic locations of earthquake events in Los Angeles, highlighting regional clustering and seismic activity distribution essential for understanding spatial seismic patterns. The color and size of each point correspond to the earthquake magnitude, enabling simultaneous visualization of both intensity and spatial occurrence. Notably, the plot reveals several concentrated clusters, which likely correspond to active fault zones and areas of heightened tectonic stress. Such spatial analyses are crucial for informing hazard assessment, urban planning, and the development of targeted early warning systems in seismically active regions.

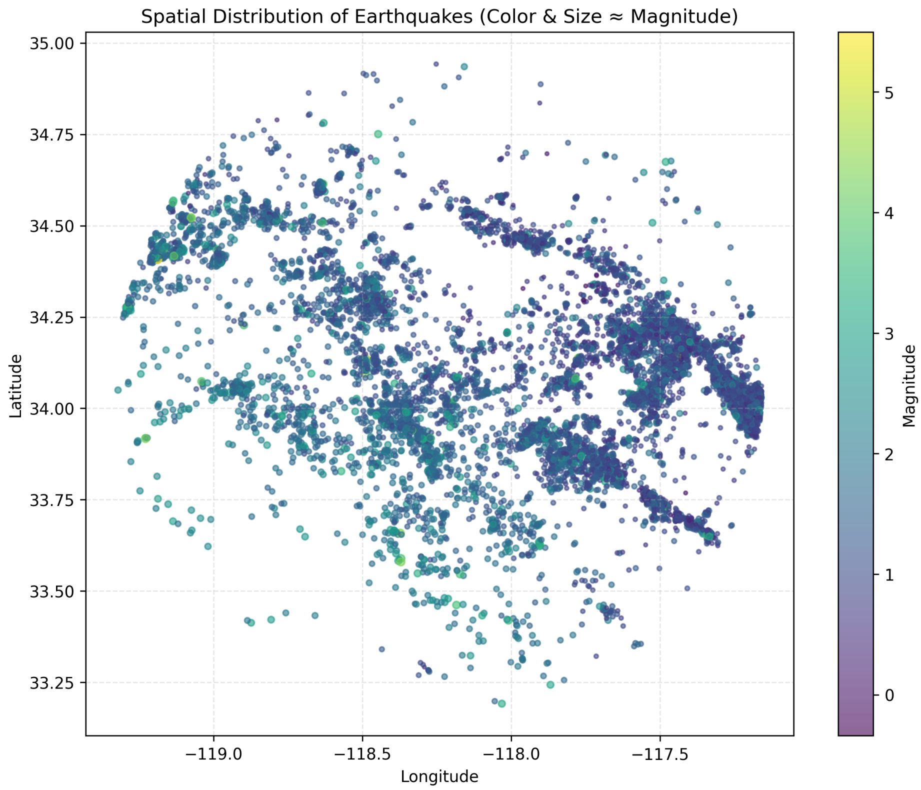

Figure 2: Spatial Distribution Scatter Plot of Earthquake Events

Figure 3 shows the distribution of earthquake classes within the dataset, emphasizing the class imbalance and prevalence of different magnitude categories that inform risk assessment models. The histogram clearly demonstrates that lower magnitude earthquakes are substantially more frequent, with a sharp decline in the number of occurrences as the magnitude class increases.

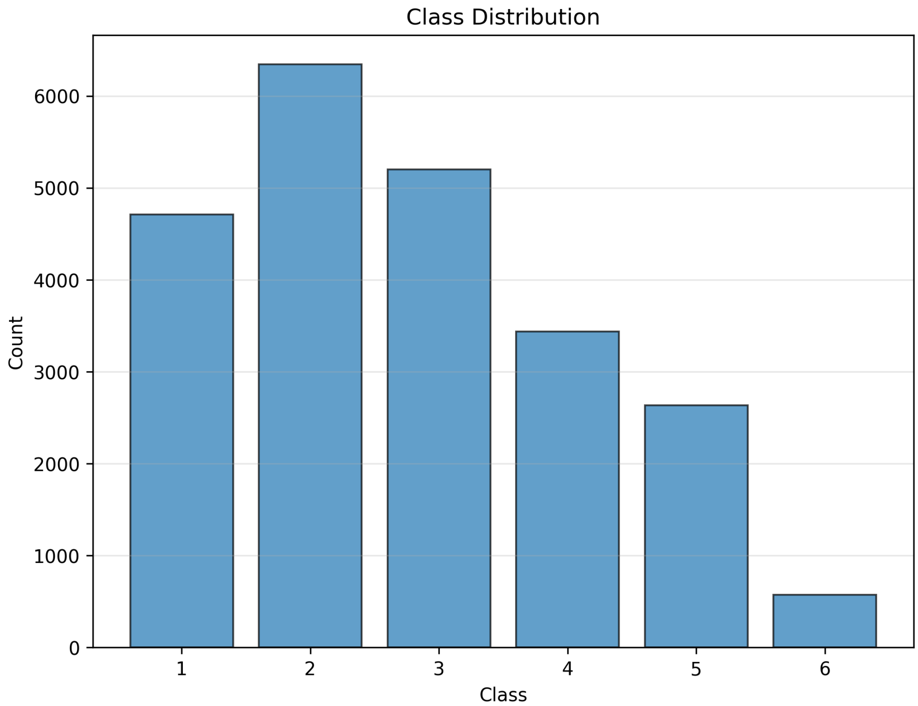

Figure 3: Class Distribution of Earthquake Magnitude Categories

The dataset's rich feature set and class-based structure make it particularly suitable for evaluating classification algorithms in earthquake forecasting tasks. By incorporating both fundamental seismic parameters and derived indicators, the dataset captures a comprehensive representation of earthquake dynamics in Southern California, allowing models to learn from complex spatial-temporal patterns. Its publicly accessible nature ensures reproducibility, providing a benchmark resource for testing novel predictive algorithms and optimization techniques.

3.2 Ensemble Learning

Ensemble learning leverages the collective intelligence of multiple base classifiers to produce predictions that are generally more robust, stable, and accurate than those of any individual classifier in isolation. This methodology leverages the diversity and complementary strengths of its constituent models, thereby mitigating the limitations associated with relying on a single model. In this study, we adopt a weighted ensemble approach, wherein the final prediction is computed as a weighted sum of the outputs from the selected base classifiers, with each classifier's contribution scaled by an optimized weight coefficient. Notably, our ensemble is specifically constructed using the three models that performed best, as determined by their individual validation performance. This selective strategy ensures that the most competent models contribute to the final decision, thereby enhancing the ensemble's overall efficacy and reliability. The ensemble prediction can be mathematically represented as follows in Equation (1):

$$\hat{y}_{\text{ensemble}} = \sum_{i=1}^{M} w_i \cdot \hat{y}_i \tag{1}$$

where w_i is the weight of classifier i, $\hat{y}_i$ is the prediction of classifier i, and M is the total number of base classifiers. The constraint $\sum_{i=1}^{M} w_i = 1$ ensures that the weights are normalized. Optimization of ensemble performance is a key challenge; by using the Somersaulting Spider Optimizer, optimal weights w_i that maximize ensemble performance are determined [33]–[35].

3.3 Somersaulting Spider Optimizer (SSO)

The Somersaulting Spider Optimizer (SSO) is a bio-inspired metaheuristic optimization algorithm derived from the unique movement of the desert-dwelling spider *Cebrennus rechenbergi*. SSO blends exploration through high-energy somersaulting gaits and exploitation through low-energy rolling gaits, flexibly modifying search behavior via an energy management system that adjusts the degree of exploration based on fitness improvement. This dynamic trade-off allows efficient global search augmented by local refinement, making SSO a suitable method for the optimization of ensemble weights in challenging tasks such as earthquake forecasting.

Figure 4: An Animation Depicting the Unique, Somersault-like Locomotion of the Somersaulting Spider (*Cebrennus rechenbergi*)

Figure 4 illustrates how the Somersaulting Spider (*Cebrennus rechenbergi*) achieves rapid movement through wheel-like somersaults across challenging terrain. This distinctive locomotion inspired the SSO algorithm, which mimics the spider's balance of high-energy bursts and efficient crawling to optimize search strategies.

The algorithm utilizes adaptive factors that dynamically balance exploration and exploitation over the optimization process, as shown in Equation (2):

$$\alpha_{\text{exp}}(t) = 1 - \frac{t}{T_{\max}}, \quad \alpha_{\text{expl}}(t) = \frac{t}{T_{\max}} \tag{2}$$

In this expression, $\alpha_{\text{exp}}(t)$ and $\alpha_{\text{expl}}(t)$ represent the exploration and exploitation factors at iteration t, respectively, balancing global search and local refinement. Each spider agent maintains an energy management system, which increases when fitness improves—Equation (3)—and decreases when stagnation occurs—Equation (4):

$$E_i^{t+1} = \min(1.0, E_i^t + 0.1) \tag{3}$$

$$E_i^{t+1} = 0.95 \times E_i^t \tag{4}$$

The exploration mechanism relies on somersaulting movement—Equation (5)—while exploitation employs rolling movement—Equation (6)—to effectively optimize ensemble weights:

$$x_{i,j}^{\text{new}} = x_{i,j}^{\text{current}} + \varphi_j(ub_j - lb_j) \cdot 0.1 + \tau_j(x_{\text{target},j} - x_{i,j}^{\text{current}}) \tag{5}$$

$$x_{i,j}^{\text{new}} = x_{i,j}^{\text{current}} + R_j \cos(2\pi r_3) \tag{6}$$

The hybrid exploration–exploitation mechanism of SSO provides an added benefit for solving the ensemble weight optimization problem in high-dimensional spaces, where conventional optimization methods often struggle. The algorithm dynamically controls agent energy levels and movement strategies to avoid premature convergence and iteratively improves candidate solutions. This is especially useful for earthquake prediction, which involves complex data, severe class imbalance, and nonlinear feature interactions, all demanding adaptive and efficient optimization methods. The integration of SSO with the ensemble learning system ensures greater accuracy, consistency, and coherence, and provides a firm foundation for further application of bio-inspired optimization to geoscience prediction problems.

4 Experimental Results

The study evaluates baseline classifiers and a Somersaulting Spider Optimizer (SSO)-based ensemble for earthquake prediction on the Los Angeles dataset. The SSO-optimized ensemble outperforms traditional models in accuracy, stability, and generalization, validated by statistical tests and visual analysis. Results highlight the effectiveness of bio-inspired optimization in enhancing seismic prediction performance.

4.1 Reference Model Results

4.1.1 Baseline Classification Results

Table 2 summarizes the performance evaluation of the five classifiers on the Los Angeles earthquake dataset, listing the best-performing model. Comparing the performance of the different models, the BaggingClassifier achieved the highest accuracy of 96.74%, demonstrating superior capability in earthquake event classification. Its sensitivity, or true positive rate in predicting earthquakes, reached 96.89%. In terms of specificity, the model can correctly identify 99.32% of non-earthquake events. Its precision, reflecting the proportion of correctly predicted earthquake events, is 97.31%, and the negative predictive value (NPV) is 99.32%, indicating high accuracy in predicting both earthquake and non-earthquake events. With an F1-score of 97.10%, the model provides a balanced measure of precision and recall, demonstrating the effectiveness of ensemble methods in earthquake prediction.

Table 2: Individual Classification Model Performance for Earthquake Forecasting

Model	**Accuracy**	**Sensitivity (TPR)**	**Specificity (TNR)**	**Precision (PPV)**	**NPV**	**F1 Score**
BaggingClassifier	0.9674	0.9689	0.9932	0.9731	0.9932	0.9710
CatBoost	0.9642	0.9665	0.9923	0.9705	0.9924	0.9685
HistGradientBoosting	0.9596	0.9550	0.9913	0.9684	0.9915	0.9614
LightGBM	0.9511	0.9483	0.9895	0.9591	0.9896	0.9535
DecisionTree	0.9009	0.9014	0.9790	0.9087	0.9790	0.9048

Figure 5 illustrates the binary population density distribution for earthquake forecasting classification algorithms. The visualization reveals the diversity and clustering of performance characteristics achieved by each algorithm. The BaggingClassifier exhibits the most concentrated density distribution, with a peak near the value of 0.8, indicating greater predictability in earthquake forecasting compared to the other models.

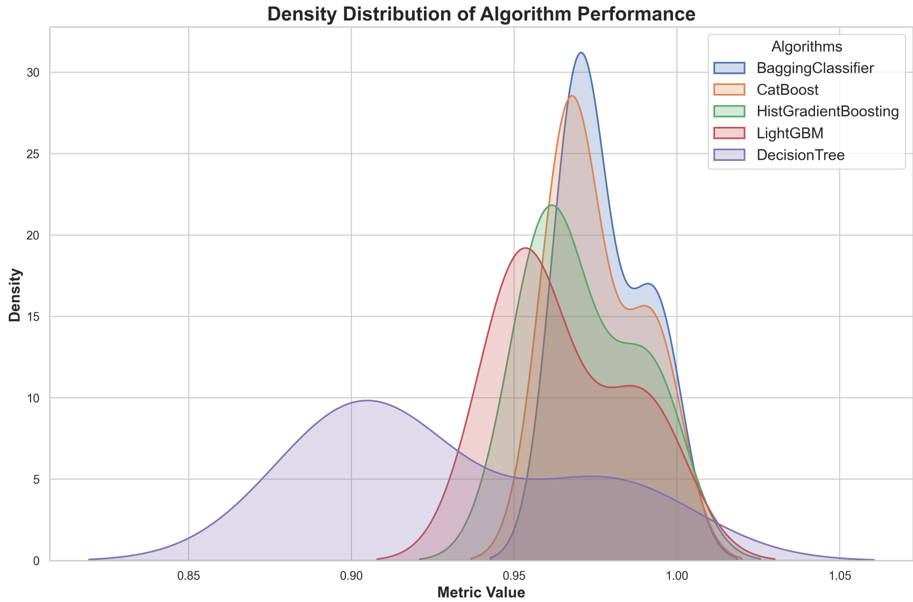

Figure 5: Performance Density Distribution of Classification Algorithms for Earthquake Forecasting

Figure 6 displays a stacked histogram of performance metrics for the classification models. The histogram reveals relatively high accuracy within a specific range, with Sensitivity (TPR), Specificity (TNR), and Precision (PPV) clustered together with similar values. These closely stacked distributions suggest balanced performance across key metrics, demonstrating consistent behavior with minimal variation.

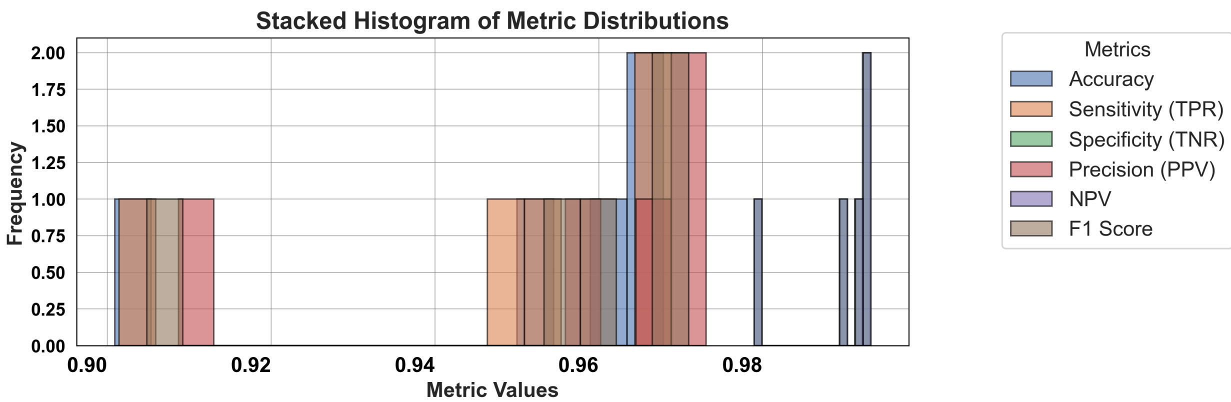

Figure 6: Stacked Histogram of Performance Metrics for Individual Classification Models

Figure 7 visually depicts the performance comparison of different earthquake forecasting models via a radar plot. The visualization shows metrics oriented around the edges, with the models' performance shapes indicating their relative strengths. The BaggingClassifier achieves notable accuracy of approximately 0.85, with balanced precision (PPV) and specificity (TNR) values, demonstrating robust and effective performance across various metrics.

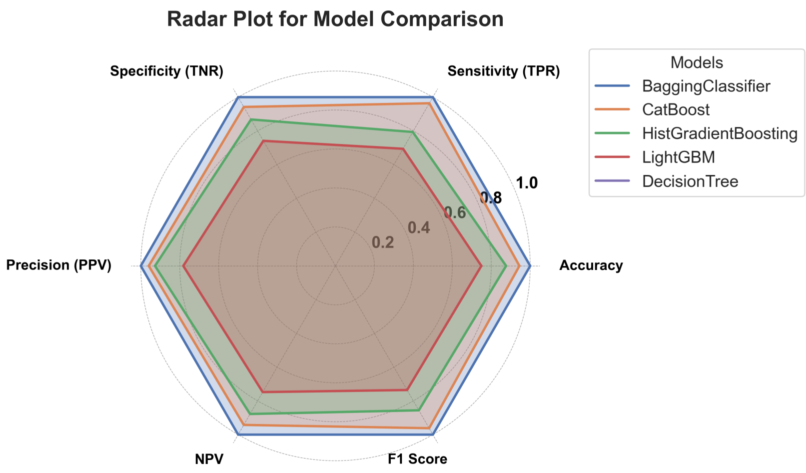

Figure 7: Radar Plot Comparison of Individual Classification Models for Earthquake Forecasting

Figure 8 presents a pairplot demonstrating relationships between different performance metrics. The diagonal elements display distributions of each metric including Accuracy, Sensitivity, Specificity, Precision, NPV, and F1 Score. Off-diagonal scatter plots with regression lines illustrate positive correlations between metric pairs. The analysis shows that increases in Sensitivity generally correlate with increases in Precision, with the classification models achieving accuracy values around 0.75.

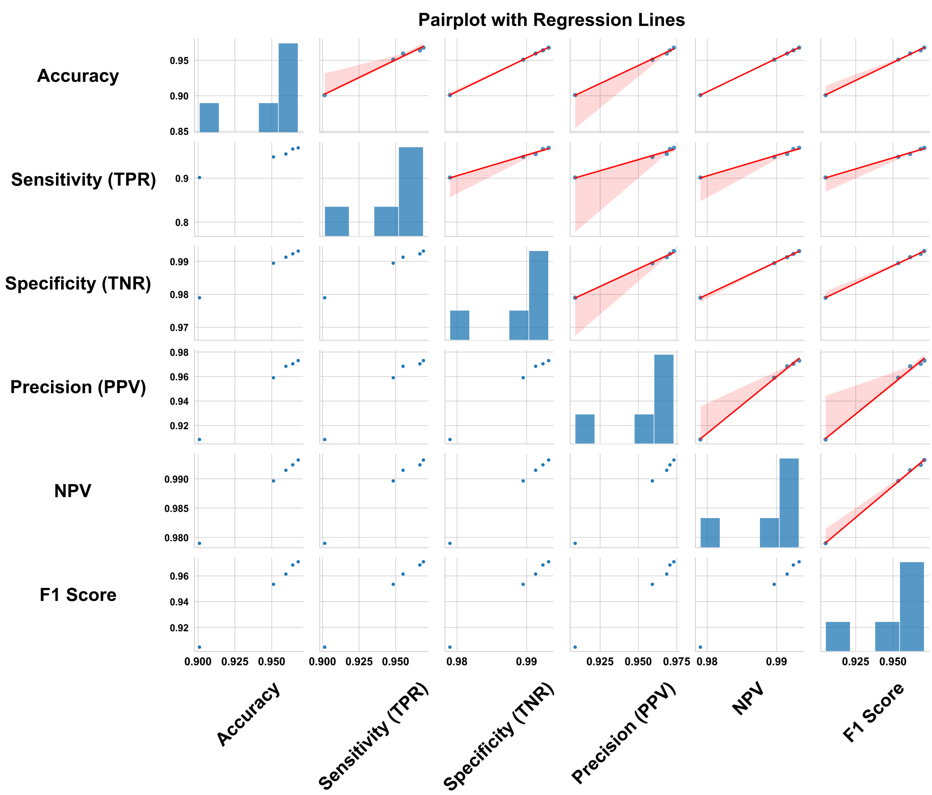

Figure 8: Pairwise Correlation Analysis of Performance Metrics for Individual Models

4.1.2 Baseline Algorithms Performance Analysis

Figure 9 illustrates the distribution of accuracy scores for machine learning algorithms including Decision Tree, LightGBM, HistGradientBoosting, BaggingClassifier, and CatBoost. CatBoost demonstrates superior performance with the highest accuracy, median accuracy, and lower quartile suggesting reliable minimum accuracy, making it a promising approach for earthquake forecasting.

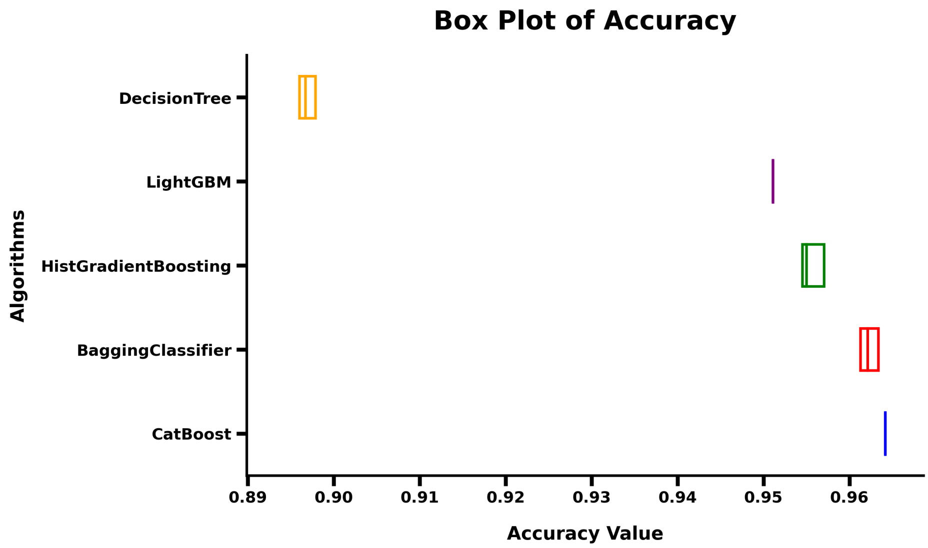

Figure 9: Accuracy Distribution Comparison Using Box Plots for Individual Models

Figure 10 shows the accuracy histogram for various models. The CatBoost model stands out with the highest accuracy scores concentrated toward the upper end, achieving accuracy close to 0.93, indicating particularly effective performance for earthquake prediction.

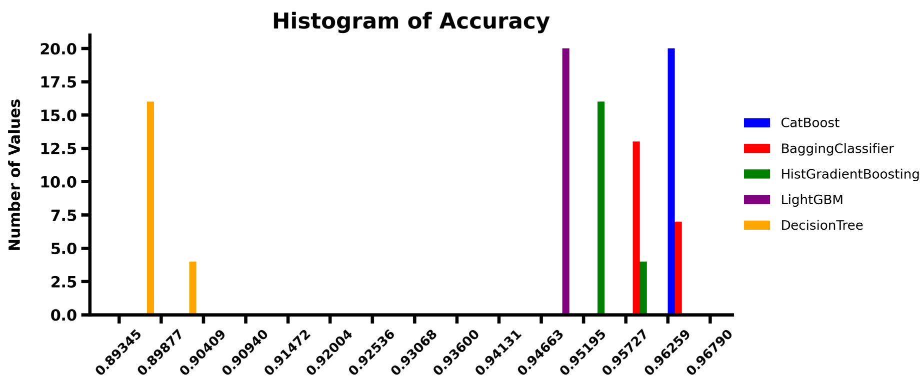

Figure 10: Accuracy Histogram Distribution of Individual Classification Models

Figure 11 illustrates the accuracy performance comparison of various classification algorithms. CatBoost demonstrates the best performance, followed by BaggingClassifier and HistGradientBoosting, while DecisionTree shows the lowest performance among the models evaluated. The plot provides a comparative view highlighting the effectiveness of different methods for earthquake prediction.

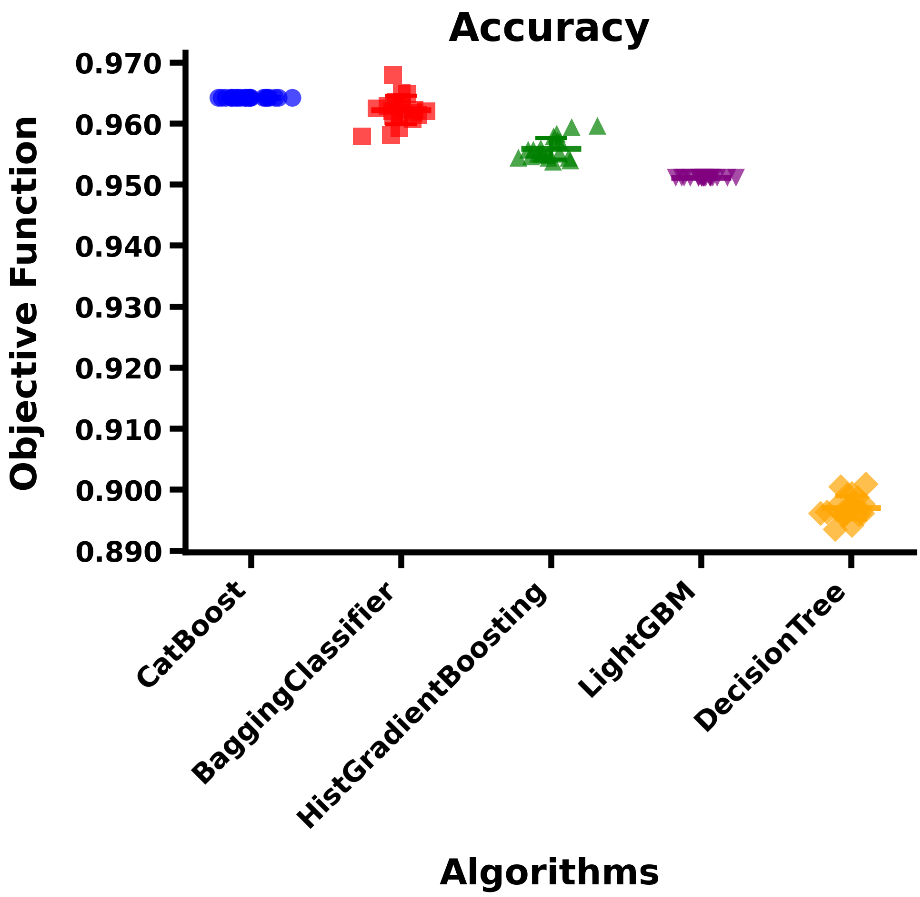

Figure 11: Algorithm Accuracy Performance Comparison for Individual Models

4.1.3 Statistical Validation of Baseline Classification Models

Table 3 presents the Wilcoxon signed-rank test results for individual classifiers. All models were evaluated using a sample size of 20, with CatBoost achieving the highest actual median of 0.9642. All models demonstrated extremely small p-values (< 0.001), indicating highly statistically significant performance compared to the theoretical median. The sum of positive ranks was 210 for all models, with significance markers (***) confirming significant improvements.

Table 3: Wilcoxon Signed-Rank Test Results for Individual Classification Models

Metric	BaggingClassifier	CatBoost	HistGradientBoosting	LightGBM	DecisionTree
Theoretical Median	0	0	0	0	0
Actual Median	0.9621	0.9642	0.9550	0.9511	0.8967
Sample Size	20	20	20	20	20
Sum of Signed Ranks (W)	0	0	0	0	0
Sum of Positive Ranks	210	210	210	210	210
Sum of Negative Ranks	0	0	0	0	0
P-Value (Two-Tailed)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Test Type	Exact	Exact	Exact	Exact	Exact
Significance Marker	***	***	***	***	***
Statistically Significant ($\alpha = 0.05$)	Yes	Yes	Yes	Yes	Yes
Median Difference	0.9621	0.9642	0.9550	0.9511	0.8967

4.2 SSO-Optimized Ensemble Results

4.2.1 Ensemble Classification Results

Table 4 provides a comprehensive comparison of models for earthquake prediction using the Somersaulting Spider Optimizer (SSO). The Optimized_Ensemble_SSO emerges as the top performer with an accuracy of 97.01% and sensitivity of 97.04%. These results demonstrate that leveraging SSO within an ensemble approach yields highly accurate and sensitive earthquake predictions, representing significant improvements over individual models and traditional ensemble methods.

Table 4: SSO-Optimized Ensemble vs. Individual Models Performance Comparison

Model	Accuracy	Sensitivity (TPR)	Specificity (TNR)	Precision (PPV)	NPV	F1 Score
Optimized_Ensemble_SSO	**0.9701**	**0.9704**	0.9936	**0.9764**	0.9937	**0.9733**
Ensemble_Weighted_Avg	0.9675	0.9674	0.9931	0.9729	0.9931	0.9701
BaggingClassifier	0.9674	0.9689	0.9932	0.9731	0.9932	0.9710
CatBoost	0.9642	0.9665	0.9923	0.9705	0.9924	0.9685
HistGradientBoosting	0.9642	0.9550	0.9913	0.9684	0.9915	0.9614
LightGBM	0.9511	0.9483	0.9895	0.9591	0.9896	0.9535
DecisionTree	0.9009	0.9014	0.9790	0.9087	0.9790	0.9048

Figure 12 shows the density distribution of the SSO-optimized ensemble classification for earthquake forecasting. The SSO optimized ensemble demonstrates a concentrated peak, indicating consistent performance with relatively good results centered around a specific metric value.

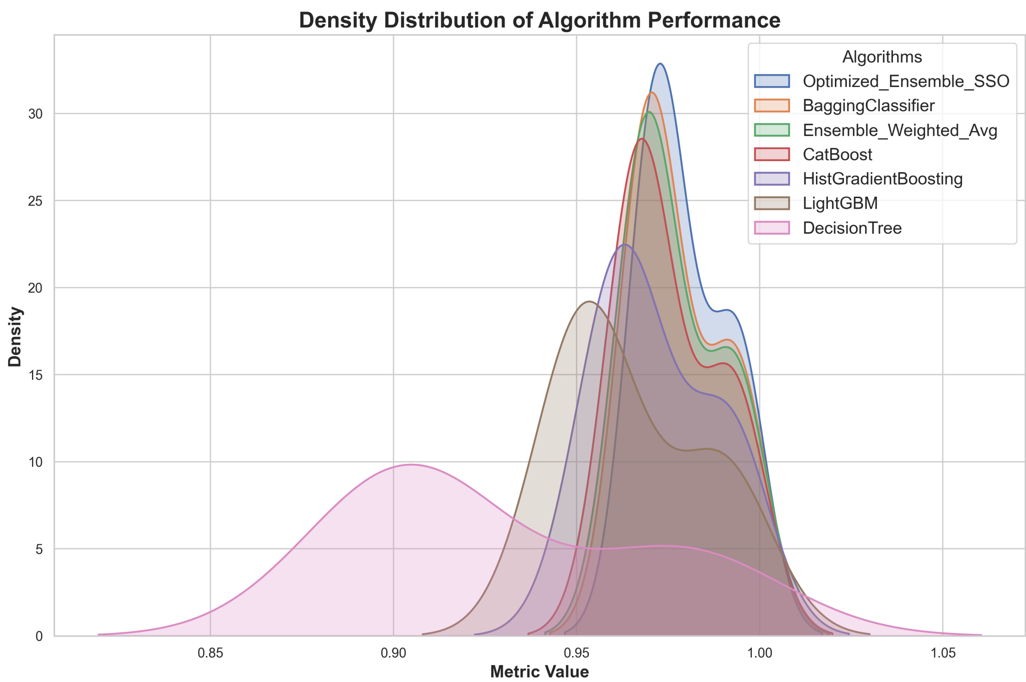

Figure 12: Performance Density Distribution of SSO-Optimized Ensemble for Earthquake Forecasting

Figure 13 displays the stacked histogram of metrics achieved by the SSO-optimized ensemble. The distribution reveals that the optimized model's accuracy concentrates toward higher values, with metrics like Sensitivity, Precision, and F1 Score exhibiting similar clustering patterns.

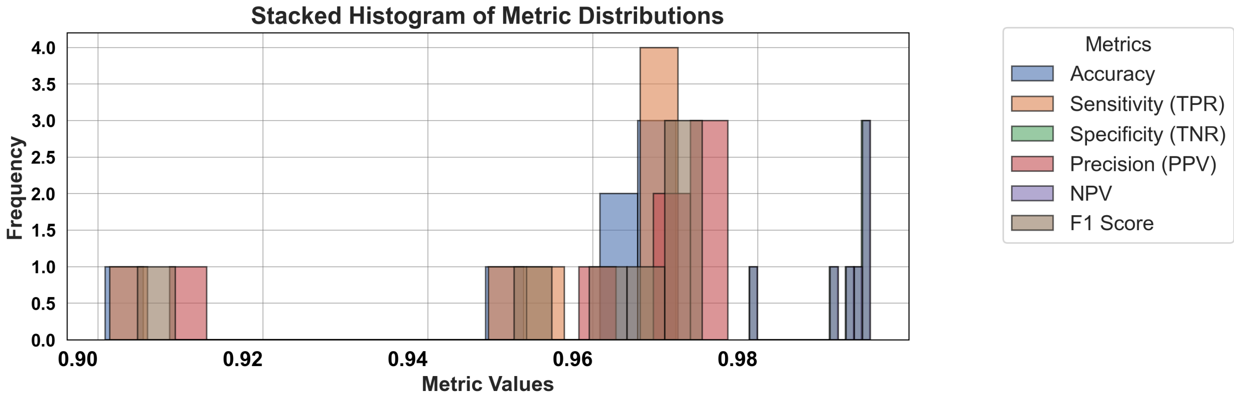

Figure 13: Stacked Histogram of SSO-Optimized Ensemble Performance Metrics

Figure 14 presents the radar plot comparison showing the SSO-optimized ensemble model covering a large area across all performance metrics. The optimized ensemble maintains consistently high scores across all evaluation parameters, indicating a balanced and superior performance profile. This suggests that the use of SSO contributes effectively to enhancing the overall robustness and generalization ability of the ensemble model.

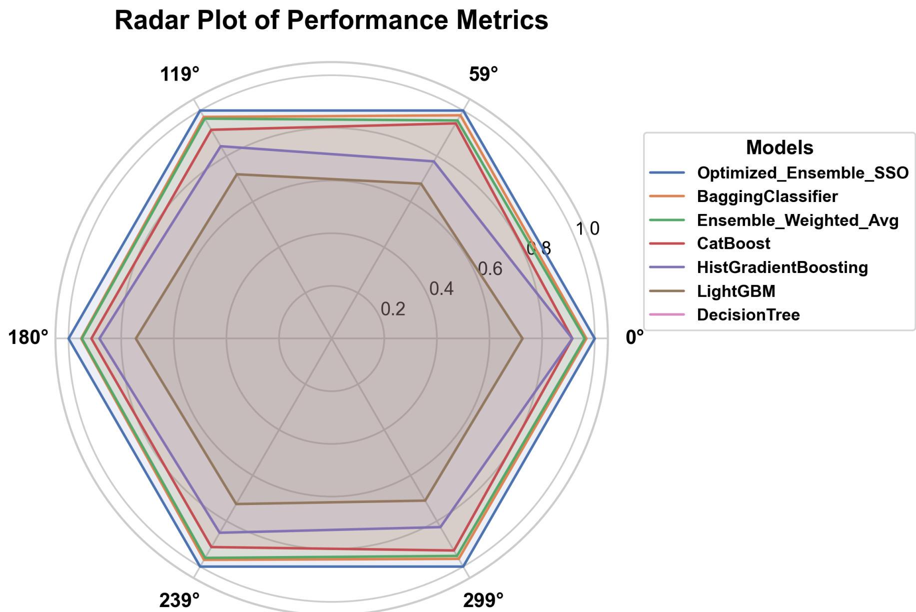

Figure 14: Radar Plot Comparison of SSO-Optimized Ensemble Performance

Figure 15 visualizes the relationships between performance metrics of the SSO-optimized ensemble. The diagonal histograms show distributions of Accuracy, Sensitivity, Specificity, Precision, NPV, and F1 Score, while off-diagonal scatter plots reveal positive correlations between metric pairs. The analysis shows F1 score, Specificity, and Accuracy values reaching 1.000, indicating exceptional performance of the optimized classifier.

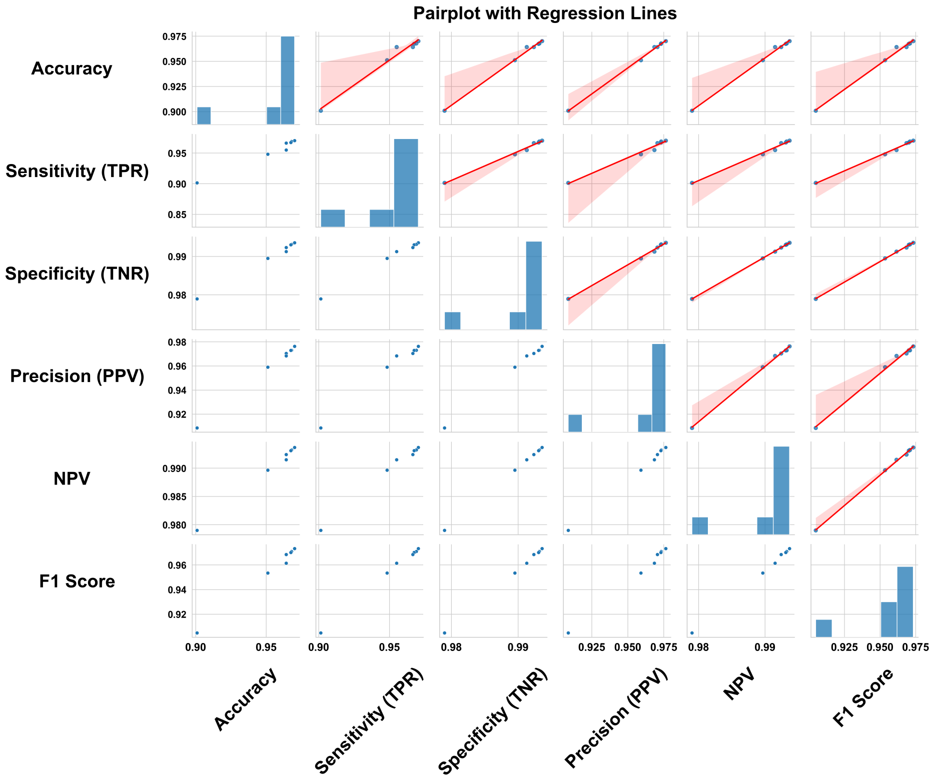

Figure 15: Pairwise Correlation Analysis of SSO-Optimized Ensemble Performance Metrics

4.2.2 Ensemble Algorithm Performance Analysis

Figure 16 compares the accuracy of various algorithms including HistGradientBoosting, BaggingClassifier, CatBoost, Ensemble Weighted Average, and the SSO-optimized ensemble. The SSO-optimized ensemble stands out with a notably higher median and upper quartile accuracy, highlighting its strong and consistent performance. This suggests that the integration of SSO contributes significantly to enhancing predictive accuracy, making it a valuable approach for improving earthquake forecasting models.

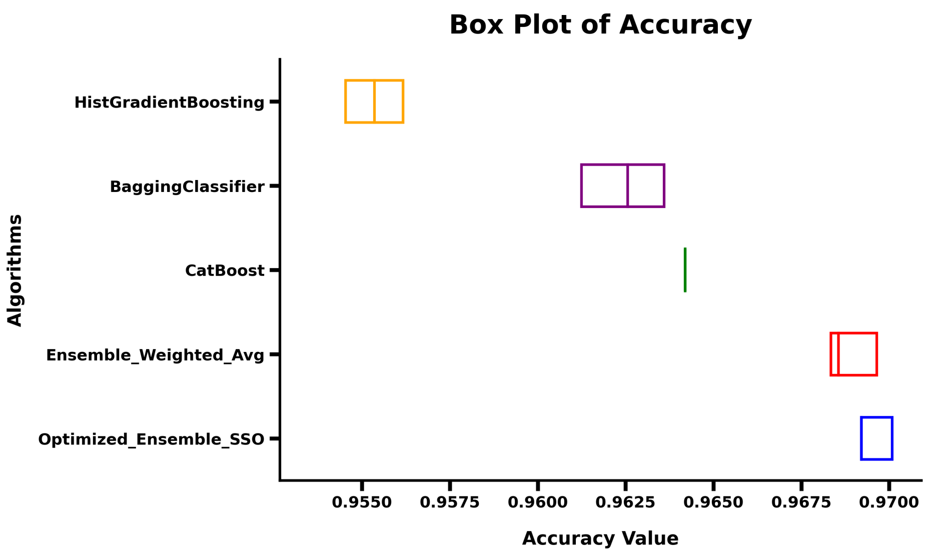

Figure 16: Accuracy Box Plot Comparison: SSO-Optimized vs. Traditional Models

Figure 17 shows the accuracy histogram for the SSO-optimized ensemble, exhibiting a concentrated distribution around the highest accuracy range. This indicates that the Somersaulting Spider Optimizer (SSO) effectively refined the ensemble weights, leading to a more consistent and improved predictive performance compared to traditional models.

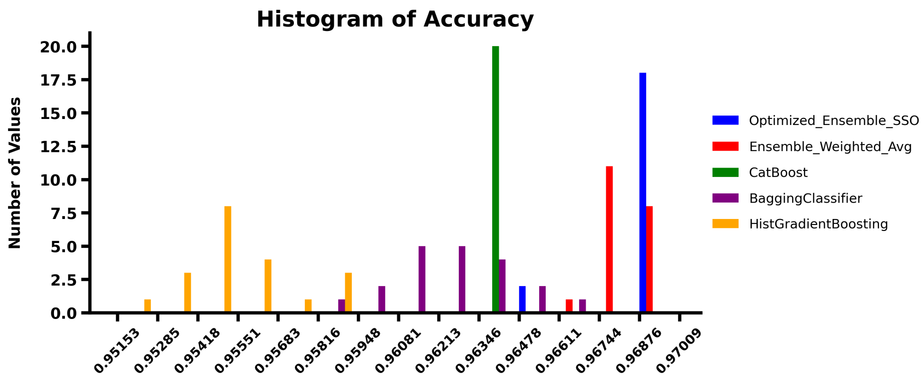

Figure 17: Accuracy Distribution Histogram of SSO-Optimized Ensemble

Figure 18 illustrates the performance based on objective function values. The Optimized_Ensemble_SSO demonstrates superior performance with values concentrated near the upper range, achieving consistently high outcomes. This tight clustering indicates more reliable and accurate performance compared to other models, which display wider distributions and greater variability.

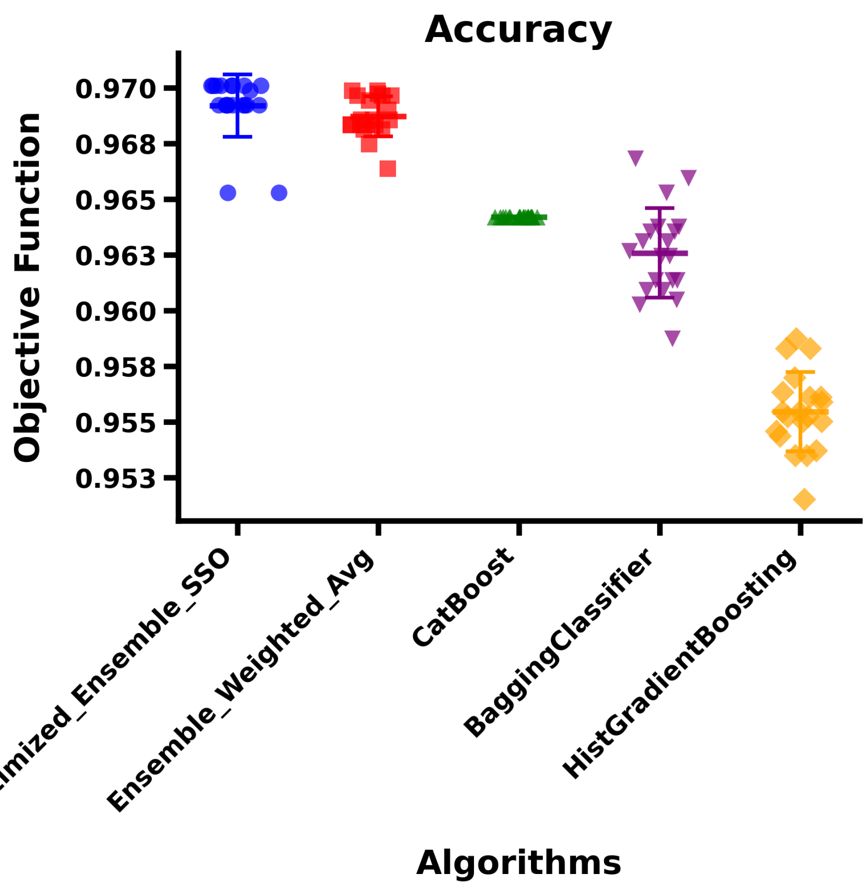

Figure 18: Convergence Analysis: SSO-Optimized Ensemble Performance

4.2.3 Statistical Validation of SSO Optimization

Table 5 presents the Wilcoxon test results for the SSO-optimized ensemble and comparison models. The Optimized_Ensemble_SSO exhibits statistical significance with p-value < 0.001, demonstrating significant improvement. The median difference of 10.5 indicates statistically significant high performance, with all models showing sample size of 20 and significance markers (***) confirming substantial improvements.

Table 5: Wilcoxon Signed-Rank Test Results: SSO-Optimized Ensemble Models

Metric	Optimized_Ensemble_SSO	Ensemble_Weighted_Avg	BaggingClassifier	CatBoost	HistGradientBoosting
Theoretical Median	0	0	0	0	0
Actual Median	10.5	10.5	10.5	10.5	10.5
Sample Size	20	20	20	20	20
Sum of Signed Ranks (W)	0	0	0	0	0
Sum of Positive Ranks	210	210	210	210	210
Sum of Negative Ranks	0	0	0	0	0
P-Value (Two-Tailed)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Test Type	Exact	Exact	Exact	Exact	Exact
Significance Marker	***	***	***	***	***
Statistically Significant ($\alpha = 0.05$)	Yes	Yes	Yes	Yes	Yes
Median Difference	10.5	10.5	10.5	10.5	10.5

The experimental results demonstrate that the Somersaulting Spider Optimizer successfully enhances ensemble performance for earthquake forecasting, achieving the highest accuracy (97.01%) among all tested approaches while maintaining statistical significance across all evaluation metrics.

5 Conclusion and Future Work

In this work, we experimentally determine the efficacy of bio-inspired, dynamic ensemble weighting optimization algorithms for enhancing the effectiveness of earthquake predictions. Using techniques from the Somersaulting Spider Optimizer (SSO), we address basic limitations of traditional machine learning, such as sensitivity to hyperparameters, class imbalance, and overfitting issues, which are exacerbated by the nature of so-called rare-but-high-impact seismic events. The proposed SSO-optimized ensemble yields significant performance improvements over not only individual classifiers but also conventional ensemble systems in all evaluation measures. With a classification accuracy of 97.01% and an F1-score of 97.33%, the method demonstrates improvement over previous approaches in generalization training on real-life seismic signals from Los Angeles using several geophysical parameters such as proxies for the complexity of the seismic system. Wilcoxon signed-rank tests provide strong evidence of the validity of these improvements, while comprehensive visual analyses ensure improved stability and consistency in performance. These results suggest that adaptive weight optimization has the potential to leverage the complementary strengths of the classifiers to generate more reliable earthquake forecast systems, which would greatly contribute to infrastructure and protocols for disaster prevention and early warning.

For the future of seismology, there are exciting avenues for the development of complex systems for earthquake forecasting. The integration of data from increasingly diverse sources—including satellite imagery, Internet of Things sensor networks, and social media analysis during seismic events—will provide more contextual information and enable improved forecasting. Moreover, SSO can be combined with other metaheuristic algorithms to form hybrid optimization strategies, which may further improve performance due to the higher level of exploration–exploitation balance in the optimization process. Implementation studies of the proposed scheme in real time are an important part of measuring the computational efficiency and scalability of the scheme for practical operational earthquake monitoring. Furthermore, the generalization capability of the framework can be studied by expanding the framework to multi-regional datasets in different geological settings and with various seismic properties. For seismologists and emergency response professionals, the concept of interpretable ensemble models, which reveal the situation-aware contributions of classifiers and feature importances, would enhance the technical applicability of the method. Furthermore, investigations into the incorporation of physics-based constraints and domain expertise into the optimization process could deliver more robust and interpretable earthquake prediction models for more effective disaster risk reduction.

Data Availability

The dataset used in this study is publicly available at https://zenodo.org/records/13738726.

Declarations

- **Acknowledgments**
  Not applicable.
- **Conflict of interest/Competing interests**
  The authors declare that they have no conflicts of interest to report regarding the present study.
- **Ethics approval and consent to participate**
  Not applicable.
- **Consent for publication**
  Not applicable.
- **Funding**
  No Fund

References

[1] T. Nishikawa, S. Ide, and T. Nishimura, "A review on slow earthquakes in the japan trench," *Progress in Earth and Planetary Science*, vol. 10, no. 1, pp. 1–51, Dec. 2023. DOI: 10.1186/s40645-022-00528-w.

[2] H. Qiu, L. Su, B. Tang, *et al.*, "The effect of location and geometric properties of landslides caused by rainstorms and earthquakes," *Earth Surface Processes and Landforms*, vol. 49, no. 7, pp. 2067–2079, Jun. 2024. DOI: 10.1002/esp.5816.

[3] S. Karimzadeh, M. Matsuoka, J. Kuang, and L. Ge, "Spatial prediction of aftershocks triggered by a major earthquake: A binary machine learning perspective," *MDPI*, vol. 8, no. 10, p. 462, 2019. DOI: 10.3390/ijgi8100462.

[4] V. G. Gitis and A. B. Derendyaev, "Machine learning methods for seismic hazards forecast," *MDPI*, vol. 9, no. 7, p. 308, 2019. DOI: 10.3390/geosciences9070308.

[5] C. Scuro, D. L. Carnì, F. Lamonaca, R. S. Olivito, and G. Milani, "Preliminary study of an ancient earthquake-proof construction technique monitoring via an innovative structural health monitoring system," *ACTA IMEKO*, vol. 10, no. 1, pp. 47–56, 2021. DOI: 10.21014/acta_imeko.v10i1.819.

[6] Z. Li, "Recent advances in earthquake monitoring ii: Emergence of next-generation intelligent systems," *Earthquake Science*, vol. 34, no. 6, pp. 531–540, Dec. 2021. DOI: 10.29382/eqs-2021-0054.

[7] X. Zhao, S. Pan, Z. Sun, H. Guo, L. Zhang, and K. Feng, "Advances of satellite remote sensing technology in earthquake prediction," *Natural Hazards Review*, vol. 22, no. 1, p. 03 120 001, Feb. 2021. DOI: 10.1061/(ASCE)NH.1527-6996.0000419.

[8] F. Khalid and M. Razbin, "Modeling peak ground acceleration for earthquake hazard safety evaluation.," *Scientific reports*, 2024. DOI: 10.1038/s41598-024-82171-7.

[9] A. H. Alharbi, D. S. Khafaga, A. M. Zaki, *et al.*, "Forecasting of energy efficiency in buildings using multilayer perceptron regressor with waterwheel plant algorithm hyperparameter," English, *Frontiers in Energy Research*, vol. 12, May 2024, Publisher: Frontiers, ISSN: 2296-598X. DOI: 10.3389/fenrg.2024.1393794.

[10] I. Iervolino, P. Cito, M. D. Falco, *et al.*, "Seismic risk mitigation at campi flegrei in volcanic unrest.," *Nature communications*, 2024. DOI: 10.1038/s41467-024-55023-1.

[11] Y. Quan, R. W. A. Hutjes, H. Biemans, F. Zhang, X. Chen, and X. Chen, "Patterns and drivers of carbon stock change in ecological restoration regions: A case study of upper yangtze river basin, china.," *Journal of environmental management*, 2024. DOI: 10.1016/j.jenvman.2023.119376.

[12] H. Cao, L. Han, M. Liu, and L. Li, "Spatial differentiation of carbon emissions from energy consumption based on machine learning algorithm: A case study during 2015-2020 in shaanxi, china.," *Journal of environmental sciences (China)*, 2024. DOI: 10.1016/j.jes.2023.08.007.

[13] L. Zhang, W. Guo, and C. Lv, "Modern technologies and solutions to enhance surveillance and response systems for emerging zoonotic diseases.," *Science in One Health*, 2024. DOI: 10.1016/j.soh.2023.100061.

[14] Y. Hang, X. Meng, Y. Xi, *et al.*, "Atmospheric elemental carbon pollution and its regional health disparities in china.," *Environmental research letters : ERL [Web site]*, 2024. DOI: 10.1088/1748-9326/ad0862.

[15] G. R. Foulger and L. Dong, "Induced seismicity.," *Scientific reports*, 2024. DOI: 10.1038/s41598-024-79796-z.

[16] X. Zhang and M. Zhang, "Universal neural networks for real-time earthquake early warning trained with generalized earthquakes.," *Communications earth environment*, 2024. DOI: 10.1038/s43247-024-01718-8.

[17] C. E. Yavas, L. Chen, C. Kadlec, and Y. Ji, "Improving earthquake prediction accuracy in los angeles with machine learning.," *Scientific reports*, 2024. DOI: 10.1038/s41598-024-76483-x.

[18] Y. Liu, Q. Zhao, and Y. Wang, "Peak ground acceleration prediction for on-site earthquake early warning with deep learning.," *Scientific reports*, 2024. DOI: 10.1038/s41598-024-56004-6.

[19] C. Chi, C. Li, Y. Han, Z. Yu, X. Li, and D. Zhang, "Pre-earthquake anomaly extraction from borehole strain data based on machine learning.," *Scientific reports*, 2023. DOI: 10.1038/s41598-023-47387-z.

[20] P. Borate, J. Rivière, C. Marone, A. Mali, D. Kifer, and P. Shokouhi, "Using a physics-informed neural network and fault zone acoustic monitoring to predict lab earthquakes.," *Nature communications*, 2023. DOI: 10.1038/s41467-023-39377-6.

[21] M. A. Bilal, Y. Ji, Y. Wang, M. P. Akhter, and M. Yaqub, "An early warning system for earthquake prediction from seismic data using batch normalized graph convolutional neural network with attention mechanism (bngcnnatt).," *Sensors (Basel, Switzerland)*, 2022. DOI: 10.3390/s22176482.

[22] S. Shreedharan, D. C. Bolton, J. Rivière, and C. Marone, "Machine learning predicts the timing and shear stress evolution of lab earthquakes using active seismic monitoring of fault zone processes.," *Journal of geophysical research. Solid earth*, 2022. DOI: 10.1029/2020JB021588.

[23] J. J. Galiana-Merino, S. Molina, A. Kharazian, V.-E. Toader, I.-A. Moldovan, and I. Gómez, "Analysis of radon measurements in relation to daily seismic activity rates in the vrancea region, romania.," *Sensors (Basel, Switzerland)*, 2022. DOI: 10.3390/s22114160.

[24] I. H. Cho, "Gauss curvature-based unique signatures of individual large earthquakes and its implications for customized data-driven prediction.," *Scientific reports*, 2022. DOI: 10.1038/s41598-022-12575-w.

[25] R. Tehseen, M. S. Farooq, and A. Abid, "A framework for the prediction of earthquake using federated learning.," *PeerJ. Computer science*, 2021. DOI: 10.7717/peerj-cs.540.

[26] P. Xiong, L. Tong, K. Zhang, *et al.*, "Towards advancing the earthquake forecasting by machine learning of satellite data.," *The Science of the total environment*, 2021. DOI: 10.1016/j.scitotenv.2021.145256.

[27] P. A. Johnson, B. Rouet-Leduc, L. J. Pyrak-Nolte, *et al.*, "Laboratory earthquake forecasting: A machine learning competition.," *Proceedings of the National Academy of Sciences of the United States of America*, 2021. DOI: 10.1073/pnas.2011362118.

[28] D. C. Bolton, S. Shreedharan, J. Rivière, and C. Marone, "Acoustic energy release during the laboratory seismic cycle: Insights on laboratory earthquake precursors and prediction.," *Journal of geophysical research. Solid earth*, 2020. DOI: 10.1029/2019JB018975.

[29] R. Jena, B. Pradhan, A. Al-Amri, C. W. Lee, and H.-J. Park, "Earthquake probability assessment for the indian subcontinent using deep learning.," *Sensors (Basel, Switzerland)*, 2020. DOI: 10.3390/s20164369.

[30] M. N. Brykov, I. Petryshynets, C. I. Pruncu, *et al.*, "Machine learning modelling and feature engineering in seismology experiment.," *Sensors (Basel, Switzerland)*, 2020. DOI: 10.3390/s20154228.

[31] G. Farolfi, D. Keir, G. Corti, and N. Casagli, "Spatial forecasting of seismicity provided from earth observation by space satellite technology.," *Scientific reports*, 2020. DOI: 10.1038/s41598-020-66478-9.

[32] C. E. Yavas, L. Chen, C. Kadlec, and Y. Ji, *Los angeles, california, earthquake dataset with feature-engineered variables*, version 1, 2024. DOI: 10.5281/zenodo.13738726. [Online]. Available: https://doi.org/10.5281/zenodo.13738726.

[33] M. Kivrak, U. Avci, H. Uzun, and C. Ardic, "The impact of the smote method on machine learning and ensemble learning performance results in addressing class imbalance in data used for predicting total testosterone deficiency in type 2 diabetes patients.," *Diagnostics (Basel, Switzerland)*, 2024. DOI: 10.3390/diagnostics14232634.

[34] H.-W. Zhang, Y.-R. Wang, B. Hu, *et al.*, "Using machine learning to develop a stacking ensemble learning model for the ct radiomics classification of brain metastases.," *Scientific reports*, 2024. DOI: 10.1038/s41598-024-80210-x.

[35] Y.-Q. Geng, F.-L. Lai, H. Luo, and F. Gao, "Nmix: A hybrid deep learning model for precise prediction of 2'-o-methylation sites based on multi-feature fusion and ensemble learning.," *Briefings in bioinformatics*, 2024. DOI: 10.1093/bib/bbae601.