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Research Paper

Earthquake Precursor Origin and AI Framework for Automatic Classification

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Abstract: Anomalous seismic, environmental, and geophysical signals are examples of observable occurrences that might serve as earthquake precursors, warning of imminent seismic events. Precise P-wave detection and earthquake source parameter estimates depend on the accurate identification of these precursors and the separation of experimental artifacts from real ground-origin signals. At three different sampling rates (50, 100, and 200 samples per second), a dataset of 429 signals was gathered from the New Abu Dabbab station and classified as either ramping, non-ramping, or mixed patterns. For the automatic categorization of P-wave signals, a Convolutional Neural Network (CNN) model was assessed in conjunction with conventional machine learning methods such as Logistic Regression, K-Nearest Neighbors, Support Vector Machine, Decision Tree, Random Forest, and XGBoost. With a 97.98% accuracy rate, the CNN model outperformed other models. By incorporating an attention mechanism, the prediction accuracy increased to 99.81%, indicating improved contextual comprehension and feature optimization in sequential seismic data. Accuracy, precision, recall, F1-score, and ROC curve analysis were used in a thorough examination, which validated the deep learning-based method's resilience. According to our findings, attention-augmented CNN models minimize mistakes in earthquake precursor identification by offering a dependable and effective framework for real-time P-wave signal categorization.

Index terms *- Earthquake precursors, P-wave detection, seismic signal classification, convolutional neural network, attention mechanism, machine learning, spectral analysis, real-time monitoring.*

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1. INTRODUCTION

Precursors of earthquakes are detectable occurrences that take place before to the onset of P-wave signals and can offer important information about upcoming seismic events. Natural ground-based processes include geomagnetic oscillations, seismic nucleation phases, nano-seismicity, gas emissions, and groundwater level changes can all provide these precursory signals. These signals are useful for early identification and risk reduction because they represent intricate subsurface interactions that occur before earthquakes. Instrumental artifacts, which are frequently produced by finite impulse response (FIR) filters in the analog-to-digital conversion stages of digitizers, can also manifest as antecedents in addition to natural sources. Often referred to as ramping patterns, these aberrations cause oscillations prior to abrupt P-wave arrivals and may compromise the precision of P-wave start timing. Calculations of

earthquake characteristics including magnitude, faulting process, and hazard assessment may be impacted by variations in automatic or manual P-wave picking caused by the diversity in precursor appearances. Early warning systems (EEW) can prevent injuries, deaths, and property damage by providing prior notification of seismic dangers through the quick and accurate detection of P-wave arrivals. To improve earthquake detection, improve real-time monitoring, and enable efficient seismic hazard mitigation measures, it is crucial to comprehend the origin and nature of various precursory signals, including how to differentiate natural patterns from instrumental artifacts.

2. LITERATURE SURVEY

1. Relationship between precursory signals and corresponding earthquakes using different spectral analysis techniques

It is debatable where the precursory signals that come before the P-waves originate because they might be the result of an instrumental influence from a digitizer or ground effect (seismic nucleation phase). These signals reduce the accuracy of earthquake parameter predictions by introducing mistakes into the automated identification of P-wave arrival timings. In order to differentiate between various kinds of precursory segments and determine if there is a connection between the presence of these precursors and the earthquakes that correspond to them, we introduced spectral analysis approaches in this study. Ten hundred and fifteen local events captured by eleven permanent seismic stations in the Egyptian National Seismic Network are subjected to these algorithms. These antecedents are present when these occurrences are manually examined. Evidence from the experiments showed that an instrumental effect was responsible for the formation of one class of these precursors. The fundamental reasons why the precursory segment appears before P-wave impulses are demonstrated in this study. Although the parameters of many events were identical, some of them had these predecessors, while others did not. For this examination, the Discrete Wavelet Transform's multi-resolution analytical details were applied. The appearance percentage for the precursory segment is 100% when huge amplitudes for high frequency P-wave detail surpass 104 counts (1 count=1 nm/s).

2. Onsite Early Prediction of Peak Amplitudes of Ground Motion Using Multi-scale STFT Spectrogram

Using single-station seismic wave measurements, on-site earthquake early warning (EEW) methods have proven effective in reducing the damage from severe earthquakes. These techniques typically use a variety of P-wave characteristics from the first seismic wave seconds after the trigger event to assess the magnitude of the earthquake and possible damage. A number of methods for forecasting peak ground amplitudes in EEW have been developed by recent developments in deep learning, especially convolutional neural networks (CNN), with encouraging results. In order to facilitate early on-site assessment of peak ground acceleration, velocity, and displacement, we suggest in this work using a multi-scale short-time frequency transform spectrogram as the input for a CNN prediction model. We compare the results with other approaches using wavelet packet transform spectrogram and a combined input of time history and Fourier spectrum, and we assess the forecast accuracy for earthquakes with low-frequency components. Compared to the other methods examined, our results show lower errors in the anticipated peak ground motion amplitudes utilizing the suggested methodology, especially with regard to peak ground velocity and displacement.

3. Earthquake early warning systems based on low-cost ground motion sensors: A systematic literature review

Earthquake early warning systems (EEWS) are essential for detecting ground shaking during an earthquake and alerting the public and authorities to take the appropriate safety measures, therefore reducing the risk of damage to persons and property. However, because to the expensive cost of sophisticated ground motion sensors, the majority of earthquake-prone countries cannot afford an EEWS. Microelectromechanical Systems (MEMS)-based low-cost ground motion sensors are becoming a feasible alternative for creating an EEWS that is both affordable and long-lasting. By reviewing the

literature, this work contributes to the field of earthquake early warning (EEW) research by investigating several approaches and methods for creating a cost-effective EEWS in different areas using MEMS-based sensors. The analysis of 59 studies suggests that low-cost MEMS-based EEWSs might emerge as a competitive option for generating reliable and accurate EEW, especially for developing countries. By increasing the sensor density, they can also serve as a support system for expensive EEWSs. This article also recommends categorizing EEWSs based on the EEW algorithm and warning category. With the aid of the proposed EEWS category, it also provides a summary of the many approaches scholars attempted to develop an EEWS. This study then discusses the challenges and intricacies of setting up and maintaining a low-cost MEMS-based EEWS, as well as possible avenues for further research to improve EEWS performance. 1) Examining node-level processing, 2) including multi-sensor support, and 3) using ground motion-based EEW algorithms for EEW creation are some of these.

4. Exceptional Electrochemical HER Performance with Enhanced Electron Transfer between Ru Nanoparticles and Single Atoms Dispersed on a Carbon Substrate

A precise regulation of metal active species' electronic structures is ideal for electrocatalysis. However, carbon with an inert surface has poor metal-support interaction, which cannot change metal nanoparticle electrical structures. We suggest scattering single metal atoms on O-doped graphene to modify the electrocatalytic activity of supported metal nanoparticles. First, computationally screen ideal atomic metal species. We next place Ru nanoparticles atop O-doped graphene adorned with single metal atoms (e.g., Fe, Co, and Ni) for hydrogen evolution reaction (HER) to confirm this hypothesis. According to theoretical expectations, such hybrid catalysts have better HER performance than state-of-the-art Pt/C. This study proposes a new way to control metal nanoparticle activity and stability for electrocatalysis.

5. Preliminary Results of Automatic P-Wave Regional Earthquake Arrival Time Picking Using Machine Learning with STA/LTA As the Input Parameters

STA/LTA is commonly used to identify earthquake arrival time. The approach simply calculates the waveform amplitude moving average ratio for short and large time periods. STA/LTA signals can identify actual events from noise, however first P wave arrival pickings are still inaccurate. This study implements Artificial Neural Network (ANN), a common machine learning approach that uses input, hidden, and output layers like the human brain. This research additionally adds input parameters with derivative signal qualities like Recursive STA/LTA and Carl STA/LTA. Event waveforms from the Agency of Meteorology, Climatology, and Geophysics were collected for processing. Regional occurrences with moment magnitude greater than 3 in Maluku, Indonesia, were selected. We then apply all STA/LTA properties to input waveforms. Additionally, we evaluated our STA/LTA using fake data and noise. Further, we manually selected P wave arrivals for ANN output. We trained arrival data in P wave phases with 100 events. The validation technique may achieve above 0.98 accuracy after 200 iterations. Final outputs indicated a 0.45-s gap between manual and ANN selection. We are able to increase the accuracy by band pass filter (0.1 – 3 Hz) all signal and improve the mean into 0.15s difference between manual picking and ANN picks.

3. METHODOLOGY

i) Proposed Work:

With a particular focus on differentiating between ramping and non-ramping P-wave patterns, the suggested system presents an attention-augmented Convolutional Neural Network (CNN) framework for accurate classification of earthquake precursor signals. To guarantee high-quality input, seismic data gathered from the New Abu Dabbab station is first preprocessed using segmentation, noise reduction, and normalization. By automatically extracting hierarchical temporal and spectral features from the seismic signals, the CNN model improves resilience across different datasets and does away with the need for human feature engineering.

In order to improve performance even further, the CNN design incorporates an attention mechanism that allows the model to choose focus on the seismic signal's most pertinent segments. By giving significant signal segments dynamic weights, this approach enhances the identification of long-range dependencies and subtle precursor patterns that traditional models sometimes overlook. A Flask-based web application is used to install the complete framework, enabling users to submit seismic data and receive real-time classification results. High accuracy, enhanced interpretability, and effective real-time processing are guaranteed by this end-to-end system, which makes it ideal for sophisticated seismic monitoring applications and earthquake early warning systems.

ii) System Architecture:

The first step in the system design is gathering seismic signals from monitoring stations as well as other earthquake precursor data. To guarantee consistency and quality of the input signals, this raw data is placed through a data preprocessing step that includes segmentation, normalization, and noise reduction. After preprocessing, the system identifies significant temporal and spectral properties of the seismic waves by feature extraction. Accurate categorization depends on these characteristics, which show important patterns including ramping behavior and fluctuations prior to P-wave arrivals.

The AI framework for automated categorization, which combines CNN and attention algorithms, is then fed the processed features. While the classification algorithm (attention-based CNN) learns intricate relationships in the data, feature selection is used in this framework to find the most pertinent features. The categorization findings are then reported by the system as either P-wave (ramping signals) or Non P-wave (non-ramping signals). For early warning applications, this architecture guarantees dependable detection of earthquake precursors, enhanced accuracy, and effective real-time processing.

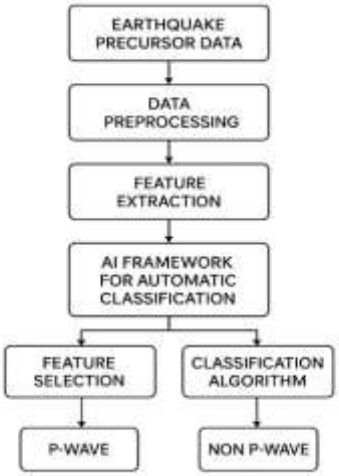


Fig.1. Proposed Architecture

iii) MODULES:

1. Importing the Packages:

This module initializes all required Python libraries for numerical computation, seismic signal processing, visualization, machine learning, deep learning, and Flask integration. It ensures the environment is ready for efficient data handling and model development.

2. Exploring the Dataset – Earthquake Precursor Dataset:

This module analyzes the seismic dataset to understand signal distribution, class labels, and sampling variations. It helps identify patterns between ramping and non-ramping signals for better model design.

3. Visualization:

This module uses graphs and plots to represent seismic signal behavior and class distribution. It highlights differences in signal patterns, noise levels, and precursor characteristics.

4. Pre-processing:

This module handles missing or inconsistent data using techniques like removal or imputation. It ensures clean and reliable input data for accurate model training.

5. Normalizing & Shuffling:

This module scales signal values to a standard range and randomly shuffles data. It improves model performance by avoiding bias and enhancing generalization.

6. Splitting Data into Train & Test:

This module divides the dataset into training and testing sets. It enables proper learning and evaluation of the model on unseen seismic signals.

7. Model Training:

This module trains various ML models (LR, KNN, SVM, DT, RF, XGBoost) and deep learning models (CNN and Attention-based CNN). It learns features to classify ramping and non-ramping signals.

8. Evaluation – Accuracy, Precision, Recall, F1-Score:

This module evaluates model performance using standard metrics. It helps identify the most accurate and reliable model for real-time classification.

9. Flask Server:

This module deploys the system as a web application. It handles user requests, processes input data, and returns classification results.

10. User Login:

This module provides authentication using credentials. It ensures secure access to the system and prevents unauthorized usage.

11. Earthquake Precursors Classification:

This module allows users to upload seismic data and get predictions. It classifies signals into ramping or non-ramping in real time.

12. Logout:

This module ends user sessions securely. It protects system access and maintains user privacy.

iv) ALGORITHMS:

1. Logistic Regression:

Linear decision boundaries underlie this supervised classification approach. It uses the sigmoid function to estimate input class probability. Effective for binary classification with linearly separable data. The model predicts categorical outcomes from independent variables quickly and cheaply. Interpretability makes it ideal for early exploration. Overfitting can be avoided by regularization. Logistic Regression maps signal properties to probability scores to identify ramping from non-ramping signals. With lesser datasets, it makes accurate, clear output judgments.

2. K-Nearest Neighbours (KNN):

This instance-based learning technique classifies new data points by comparing them to their most comparable feature space records. How many neighbors are considered depends on k, and majority vote decides class. It works effectively for nonlinear distributions without model training. The approach evaluates similarity using Euclidean or Manhattan distance metrics. Aligning unknown signals with labeled examples helps find different patterns between categories. It works well with normalized input features but slowly on big datasets.

3. SVM:

Support Vector Machine creates ideal hyperplanes to distinguish classes with greatest margin. It works for linear and non-linear classification utilizing kernel functions like radial basis or polynomial. SVM reduces classification mistakes in high-dimensional data by focusing on support vectors. It resists overfitting when the margin is obvious. SVM can recognize minor signal characteristics and complicated

patterns. It works for small to larger datasets with obvious category separation. The model performs best with correct kernel and regularization settings.

4. Decision Tree:
Hierarchical classification method Decision Tree separates data by feature thresholds to produce branches and decision nodes. Internal nodes reflect test conditions, while leaf nodes show class results. Interpretation and decision logic visualization are simple. It finds categorization characteristics for categorical and continuous data. Decision Trees exhibit important patterns in nonlinear connections. However, without trimming, they overfit. This approach categorizes signals by examining feature changes at various levels for quick predictions.

5. Random Forest:
This ensemble learning method constructs numerous Decision Trees using random data and characteristics. Majority vote across all trees produces final forecasts. Variance reduction and overfitting mitigation improve prediction accuracy. Random Forest handles missing values and high-dimensional data well. It accurately classifies complicated feature space interactions. Important input parameters are identified via feature significance ranking. It has good signal differentiation performance and is robust to outliers and noise. Though computationally demanding, it generalizes better than single-tree models.

6. XGBoost
Extreme Gradient Boosting (XGBoost) systematically constructs decision trees to fix faults from prior models. Gradient descent minimizes loss functions and regularization controls overfitting. XGBoost analyzes structured data and computes parallelly, speeding training. For huge datasets, it captures complicated feature relationships and improves forecast accuracy. Shrinkage and subsampling boost performance. XGBoost is known for managing noisy data and getting better accuracy than other approaches.

7. Proposed CNN:
Convolutional layers automatically extract spatial and temporal patterns from input data in the proposed CNN. Without manual feature engineering, it learns hierarchies. To anticipate, CNN effectively analyzes raw data utilizing filters, pooling layers, and fully linked layers. It detects small signal fluctuations, making it useful for pattern identification. Deep learning enables adaptive learning of complicated features for categorization. CNN improves accuracy and performance with huge datasets and backpropagation. Deep architectures with good feature extraction make early detection reliable.

8. Attention+CNN Extension:
Automatic feature extraction and targeted information weighting are employed in the extended CNN with attention method. Convolutional layers record local patterns, whereas attention modules highlight classification-relevant elements. Impactful areas are prioritized by this integration, improving essential signal segment detection. Highlighting results-influencing regions improves interpretability. The model adjusts to input patterns and enhances signal sensitivity. Attention-enhanced CNNs make learning robust, minimize misclassification, and increase signal differentiation. In contrast to CNN structures, it provides deeper insights.

4. EXPERIMENTAL RESULTS

Experimental findings show that the Attention-based CNN model classifies earthquake precursor signals better than classical machine learning and CNN. Logistic Regression, KNN, SVM, Decision Tree, Random Forest, XGBoost, CNN, and extended Attention-CNN were tested on 429 seismic waves. Attention-CNN performed best with 99.81% accuracy, compared to 97.98% for the regular CNN model. This increase shows how well the attention mechanism captures crucial temporal relationships and emphasizes relevant signal segments for ramping and non-ramping pattern categorization.

Additionally, accuracy, recall, F1-score, and ROC analysis corroborate the model's robustness and dependability. The attention mechanism prioritizes relevant precursor patterns and reduces noise to improve feature representation. The Flask-based web solution also allows users to submit seismic data and get quick categorization results. The extended system is ideal for sophisticated seismic early warning systems because to its accuracy, generalization, and real-time performance.

Accuracy: The ability of a test to differentiate between healthy and sick instances is a measure of its accuracy. Find the proportion of analysed cases with true positives and true negatives to get a sense of the test's accuracy. Based on the calculations:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying the following formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

Recall: The recall of a model is a measure of its capacity to identify all occurrences of a relevant machine learning class. A model's ability to detect class instances is shown by the ratio of correctly predicted positive observations to the total number of positives.

$$Recall = \frac{TP}{(FN + TP)}$$

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic..

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$



Fig 2:Not Ramping



Fig 3:Ramping Detected



Fig 4:Accuracy Graph

5. CONCLUSION

Early warning and seismic mitigation require accurate earthquake precursor detection and categorization. The study showed that distinguishing real ground-origin P-wave signals from instrumental artifacts improves precursor analysis reliability. The method identified ramping patterns linked to aberrant P-wave activity by collecting and analyzing 429 data from the New Abu Dabbab station at several sample rates. Traditional machine learning methods classified signals, but the convolutional neural network (CNN) performed best with 97.98% accuracy. Adding an attention mechanism to the CNN architecture improved prediction accuracy to 99.81%. This shows that attention-based deep learning models may capture complicated temporal correlations and highlight crucial seismic data elements for reliable real-time P-wave categorization. The findings show that enhanced feature optimization and contextual awareness may greatly minimize earthquake precursor detection mistakes. Deep learning with accurate seismic monitoring can improve early earthquake identification and risk mitigation measures, as shown in the study.

6. FUTURE SCOPE

The categorization system may be expanded by adding more real-time seismic data from many monitoring stations in different locations. Adding precursors like electromagnetic fluctuations, temperature changes, and gas emissions improves prediction. More accurate anomaly detection and signal denoising would decrease false alerts. The system may be adjusted for real-time deployment and computing efficiency to identify urgent situations faster. Using adaptive learning to modify the model with fresh seismic patterns might increase long-term dependability. During pre-seismic monitoring, improving visualization and alert interfaces can speed interpretation and decision-making.

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