Origin of Earthquake Precursors and AI Framework for Automated Classification

K. Baby Ramya [1], K. Pavani [2], A. Azees [3]

#1 Assistant Professor in the Department of MCA, SRK Institute of Technology, Vijayawada

#2 Assistant Professor & Head of Department of MCA, SRK Institute of Technology, Vijayawada.

#3 Student in the Department of MCA, SRK Institute of Technology, Vijayawada

Abstract: Examples of visible phenomena that might act as earthquake precursors, alerting people to impending seismic events, include anomalous seismic, environmental, and geophysical signals. Accurately identifying these precursors and separating actual ground-origin signals from experimental artifacts are essential for precise P-wave detection and earthquake source parameter estimation. A dataset of 429 signals was collected from the New Abu Dabbab station at three distinct sampling rates (50, 100, and 200 samples per second) and categorized as either ramping, non-ramping, or mixed patterns. A Convolutional Neural Network (CNN) model was evaluated in combination with traditional machine learning techniques as Logistic Regression, K-Nearest Neighbors, Support Vector Machine, Decision Tree, Random Forest, and XGBoost for the automated classification of P-wave data. The CNN model fared better than other models, with an accuracy rate of 97.98%. The prediction accuracy rose to 99.81% with the addition of an attention mechanism, suggesting better contextual understanding and feature optimization in sequential seismic data. A comprehensive investigation including accuracy, precision, recall, F1-score, and ROC curve analysis confirmed the robustness of the deep learning-based approach. Our results show that by providing a reliable and efficient framework for real-time P-wave signal classification, attention-augmented CNN models reduce errors in earthquake precursor detection.

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

1. INTRODUCTION

Earthquake precursors are observable phenomena that occur prior to the start of P-wave signals and can provide crucial information about impending seismic events. These precursory signals can be produced by natural ground-based processes such as groundwater level fluctuations, gas emissions, nano-seismicity, seismic nucleation phases, and geomagnetic oscillations. Because these signals reflect complex subsurface interactions that take place before to earthquakes, they are helpful for early diagnosis and risk mitigation. In addition to natural causes, instrumental artifacts, which are often generated by finite impulse response (FIR) filters in the analog-to-digital conversion stages of digitizers, can also appear as antecedents. These aberrations, also known as ramping patterns, might affect the accuracy of P-wave start timing by causing oscillations before sudden P-wave arrivals. Variations in automatic or manual P-wave picking brought on by the diversity of precursor appearances may affect calculations of earthquake features such as magnitude, faulting process, and hazard assessment. By promptly and accurately detecting P-wave arrivals, early warning systems (EEW) can avoid injuries, fatalities, and property damage. Understanding the origin and nature of distinct precursory signals, especially how to distinguish natural patterns from instrumental artifacts, is essential for enhancing earthquake detection, improving real-time monitoring, and enabling effective seismic hazard mitigation methods.

2. LITERATURE SURVEY

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

The origin of the precursory signals that precede the P-waves is controversial since they might be the consequence of ground effect (seismic nucleation phase) or artificial impact from a digitizer. These signals cause errors in the automated detection of P-wave arrival times, which lowers the accuracy of earthquake parameter forecasts. In this work, we presented spectral analysis techniques to distinguish between distinct types of precursory segments and ascertain if the presence of these precursors and the corresponding earthquakes are related. These algorithms are applied to 115 local occurrences recorded by eleven permanent seismic stations in the Egyptian National Seismic Network. When these occurrences are manually inspected, these antecedents are found. The results of the studies demonstrated that one class of these precursors was formed as a result of an instrumental influence. This study illustrates the basic causes of the precursory segment's appearance prior to P-wave impulses. Some events had these precursors, but others did not, even if the criteria of many of them were the same. The multi-resolution analytical details of the Discrete Wavelet Transform were used for this analysis. When enormous amplitudes for high frequency P-wave detail exceed 104 counts (1 count=1 nm/s), the appearance percentage for the precursory segment is 100%.

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

On-site earthquake early warning (EEW) techniques have demonstrated efficacy in mitigating the damage caused by large earthquakes by utilizing single-station seismic wave data. To determine the size of the earthquake and potential damage, these methods usually employ a range of P-wave characteristics from the first seismic wave seconds following the trigger event. Recent advances in deep learning, particularly convolutional neural networks (CNN), have produced a number of techniques for predicting peak ground amplitudes in EEW with promising outcomes. In this study, we propose to use a multi-scale short-time frequency transform spectrogram as the input for a CNN prediction model to enable early on-site evaluation of peak ground acceleration, velocity, and displacement. We evaluate the forecast accuracy for earthquakes with low-frequency components and compare the findings with alternative methods utilizing a wavelet packet transform spectrogram and a combined input of time history and Fourier spectrum. Our findings demonstrate reduced errors in the expected peak ground motion amplitudes using the proposed methodology when compared to the other approaches investigated, particularly with respect to peak ground velocity and displacement.

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

In order to identify ground shaking during an earthquake and notify the public and authorities to take the necessary safety precautions, earthquake early warning systems (EEWS) are crucial for lowering the danger of property and human damage. However, most earthquake-prone nations cannot afford an EEWS because to the high expense of advanced ground motion sensors. Low-cost ground motion sensors based on Microelectromechanical Systems (MEMS) are emerging as a viable option for developing an EEWS that is both long-lasting and reasonably priced. Through a study of the literature, this work advances the field of earthquake early warning (EEW) research by examining several strategies and techniques for developing an affordable EEWS in various locations utilizing MEMS-based sensors. Low-cost MEMS-based EEWSs may become a competitive option for producing accurate and dependable EEW, particularly for poor nations, according to the study of 59 research. They can also function as a support system for pricey EEWSs by raising the sensor density. Additionally, this page suggests classifying EEWSs according to the warning category and EEW algorithm. It also offers an overview of the many methods researchers have tried to create an EEWS with the help of the suggested EEWS category. The difficulties and complexities of establishing and sustaining a low-cost MEMS-based EEWS are then covered in this work, along with potential directions for further investigation to enhance EEWS performance. These include: 1) looking at node-level processing; 2) including multi-sensor support; and 3) creating EEWs utilizing ground motion-based EEW algorithms.

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

Electrocatalysis requires careful control of the electronic structures of metal active species. Nevertheless, the weak metal-support interaction of carbon with an inert surface prevents the electrical structures of metal nanoparticles from changing. To alter the electrocatalytic activity of supported metal nanoparticles, we propose scattering individual metal atoms on O-doped graphene. Start by screening ideal atomic metal species computationally. To verify this theory, we then install Ru nanoparticles on top of O-doped graphene decorated with single metal atoms (such as Fe, Co, and Ni) for the hydrogen evolution process (HER). Theoretically, these hybrid catalysts outperform cutting-edge Pt/C in terms of HER performance. This work suggests a novel approach to regulate the stability and activity of metal nanoparticles 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 frequently used to determine the arrival time of earthquakes. For both short and long time intervals, the method merely computes the waveform amplitude moving average ratio. First P wave arrival pickings are still erroneous, however STA/LTA signals can distinguish real events from noise. The Artificial Neural Network (ANN), a popular machine learning technique that mimics the input, hidden, and output layers of the human brain, is used in this study. Additionally, input parameters with derivative signal characteristics such as Carl STA/LTA and Recursive STA/LTA are added in this study. For processing, event waveforms were gathered from the Agency of Meteorology, Climatology, and Geophysics. In Maluku, Indonesia, regional events with moment magnitudes larger than three were chosen. The input waveforms are then subjected to all STA/LTA qualities. We also used noise and fictitious data to assess our STA/LTA. Additionally, we chose P wave arrivals by hand for the ANN output. We used 100 events to train arrival data in P wave phases. After 200 iterations, the validation method may reach an accuracy of more than 0.98. The final results showed that the difference between manual and ANN selection was 0.45 seconds. By using a band pass filter (0.1–3 Hz) on all signals, we can enhance the accuracy and reduce the mean disparity between ANN and manual choices to 0.15 seconds.

3. METHODOLOGY

i) Proposed Work:

The proposed system offers an attention-augmented Convolutional Neural Network (CNN) architecture for precise classification of earthquake precursor signals, with an emphasis on distinguishing between ramping and non-ramping P-wave patterns. Seismic data collected from the New Abu Dabbab station is first preprocessed utilizing segmentation, noise reduction, and normalization to ensure high-quality input. The CNN approach eliminates the requirement for human feature engineering and increases robustness across various datasets by automatically extracting hierarchical temporal and spectral characteristics from the seismic signals.

The CNN architecture includes an attention mechanism that enables the model to select emphasis on the most relevant regions of the seismic signal in order to further enhance performance. This method improves the detection of long-range dependencies and subtle precursor patterns that conventional models occasionally miss by assigning dynamic weights to important signal segments. The entire framework is installed via a Flask-based web application that allows users to enter seismic data and get real-time classification results. This end-to-end system is perfect for complex seismic monitoring applications and earthquake early warning systems because it ensures high accuracy, improved interpretability, and efficient real-time processing.

ii) System Architecture:

Collecting seismic signals from monitoring stations and other earthquake precursor data is the initial stage in the system design process. This raw data is put through a data preparation stage that involves segmentation, normalization, and noise reduction to ensure consistency and quality of the input signals. Following preprocessing, the system uses feature extraction to find important temporal and spectral characteristics of the seismic waves. These features, which exhibit significant patterns including ramping behavior and variations before P-wave arrivals, are essential for accurate classification.

The processed characteristics are then supplied into the AI framework for automatic classification, which combines CNN and attention algorithms. In this framework, feature selection is utilized to identify the most relevant aspects while the classification algorithm (attention-based CNN) learns complex correlations in the data. The algorithm then reports the classification results as either P-wave (ramping signals) or Non-P-wave (non-ramping signals). This architecture ensures reliable earthquake precursor identification, improved accuracy, and efficient real-time processing for early warning applications.

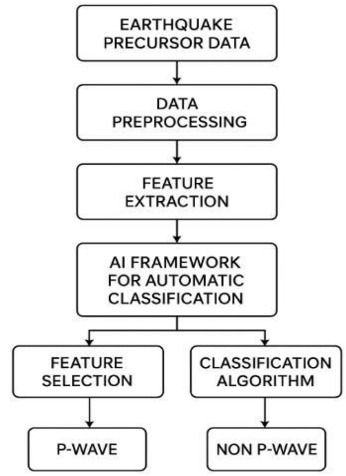

Fig.1. Proposed Architecture

iii) MODULES:

1. Importing the Packages:

All necessary Python libraries for numerical computing, seismic signal processing, machine learning, deep learning, visualization, and Flask integration are initialized in this module. It guarantees that the setting is prepared for effective data processing and model creation.

2. Exploring the Dataset – Earthquake Precursor Dataset:

In order to comprehend signal distribution, class labels, and sample changes, this module examines the seismic dataset. For improved model design, it assists in finding patterns between ramping and non-ramping signals.

3. Visualization:

Plots and graphs are used in this module to illustrate the distribution of classes and the behavior of seismic signals. It draws attention to variations in precursor properties, noise levels, and signal patterns.

4. Pre-processing:

This module uses methods like imputation and removal to deal with inconsistent or missing data. For precise model training, it guarantees clean and trustworthy input data..

5. Normalizing & Shuffling:

This module shuffles data at random and scales signal values to a standard range. By preventing bias and boosting generalization, it enhances model performance.

6. Splitting Data into Train & Test:

The dataset is separated into training and testing sets using this module. It makes it possible for the model to be properly learned and evaluated on unseen seismic data.

7. Model Training:

This module trains different deep learning models (CNN and Attention-based CNN) and machine learning models (LR, KNN, SVM, DT, RF, XGBoost). In order to distinguish between ramping and non-ramping signals, it learns characteristics.

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

This module uses common metrics to assess the model's performance. It assists in determining the most dependable and accurate model for real-time categorization.

9. Flask Server:

The system is deployed as a web application via this module. It processes incoming data, responds to user queries, and provides categorization outcomes.

10. User Login:

Credentials are used for authentication in this module. It prevents unwanted use and guarantees safe system access.

11. Earthquake Precursors Classification:

Users can submit seismic data and receive forecasts using this module. In real time, it categorizes signals as either ramping or non-ramping.

12. Logout:

This module safely terminates user sessions. It preserves user privacy and safeguards system access.

iv) ALGORITHMS:

1. Logistic Regression:

This supervised classification method is based on linear decision boundaries. It estimates the probability of the input class using the sigmoid function. useful for binary classification when the data is linearly separable. The model swiftly and affordably forecasts categorical results from independent variables. It is perfect for early exploration because of its interpretability. Regularization helps prevent overfitting. To distinguish ramping signals from non-ramping signals, logistic regression transfers signal characteristics to probability scores. It provides precise, understandable output decisions with smaller datasets.

2. K-Nearest Neighbours (KNN):

By comparing fresh data points to their most similar feature space records, this instance-based learning method classifies them. The majority vote determines class, and k determines how many neighbors are taken into account. Without model training, it performs well for nonlinear distributions. The method uses Manhattan or Euclidean distance metrics to assess similarity. Finding distinct patterns between categories is aided by aligning unknown signals with labeled samples. It performs poorly on large datasets but well with normalized input characteristics.

3. SVM:

The best hyperplanes to separate classes with the largest margin are produced using Support Vector Machines. It uses kernel functions such as polynomial or radial basis for both linear and non-linear classification. By concentrating on support vectors, SVM lowers classification errors in high-dimensional data. When the margin is clear, it resists overfitting. SVM is capable of identifying complex patterns and subtle signal features. It is effective for datasets of all sizes with clear category separation. When the kernel and regularization settings are set correctly, the model operates optimally.

4. Decision Tree:
Method of hierarchical categorization Decision trees create branches and decision nodes by dividing data according to feature criteria. Leaf nodes display class results, whereas internal nodes represent test conditions. Decision logic visualization and interpretation are easy. For both continuous and categorical data, it determines classification properties. Important patterns in nonlinear connections may be seen in decision trees. They overfit, too, if they aren't trimmed. In order to make fast predictions, this method classifies signals by looking at feature changes at several levels.

5. Random Forest:

This ensemble learning technique uses random data and attributes to build several Decision Trees. Final projections are determined by a majority vote across all trees. Prediction accuracy is increased by variance reduction and overfitting mitigation. High-dimensional data and missing values are easily handled by Random Forest. Complex feature space interactions are correctly classified by it. Feature importance ranking is used to identify important input parameters. It performs well in signal separation and is resistant to noise and outliers. It outperforms single-tree models in terms of generalization despite being computationally intensive.

6. XGBoost
To address flaws in previous models, Extreme Gradient Boosting (XGBoost) methodically builds decision trees. Regularization prevents overfitting, whereas gradient descent reduces loss functions. XGBoost speeds up training by analyzing structured data and performing parallel computations. It increases forecast accuracy and captures complex feature interactions for large datasets. Performance is improved via subsampling and shrinkage. XGBoost is renowned for handling noisy data and achieving higher accuracy than alternative methods.

7. Proposed CNN:
In the suggested CNN, convolutional layers automatically extract temporal and spatial patterns from input data. It learns hierarchies without the need for manual feature engineering. CNN uses filters, pooling layers, and fully connected layers to evaluate raw data in an efficient manner. It is helpful for identifying patterns since it can detect minute signal variations. Adaptive learning of complex features for classification is made possible by deep learning. CNN uses backpropagation and large datasets to increase performance and accuracy. Reliable early detection is made possible by deep architectures with strong feature extraction.

8. Attention+CNN Extension:
The extended CNN with attention approach uses targeted information weighting and automatic feature extraction. While attention modules draw attention to aspects that are significant to classification, convolutional layers capture local patterns. This integration improves crucial signal segment detection by prioritizing impactful locations. Interpretability is enhanced when results-influencing areas are highlighted. The model improves signal sensitivity and adapts to input patterns. Attention-enhanced CNNs improve signal distinction, reduce misclassification, and strengthen learning. It offers more profound insights than CNN frameworks.

4. EXPERIMENTAL RESULTS

According to experimental results, the Attention-based CNN model outperforms CNN and traditional machine learning in the classification of earthquake precursor signals. 429 seismic waves were used to evaluate Logistic Regression, KNN, SVM, Decision Tree, Random Forest, XGBoost, CNN, and extended Attention-CNN. With an accuracy of 99.81%, Attention-CNN outperformed the standard CNN model, which had an accuracy of 97.98%. This increase demonstrates how successfully the attention mechanism highlights essential signal segments for the classification of ramping and non-ramping patterns and captures important temporal correlations.

Furthermore, the model's robustness and reliability are confirmed by accuracy, recall, F1-score, and ROC analysis. To enhance feature representation, the attention mechanism lowers noise and gives priority to pertinent precursor patterns. Users may also enter seismic data and receive fast classification results via the Flask-based online solution. The expanded system's precision, generalization, and real-time performance make it perfect for complex seismic early warning systems.

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..

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

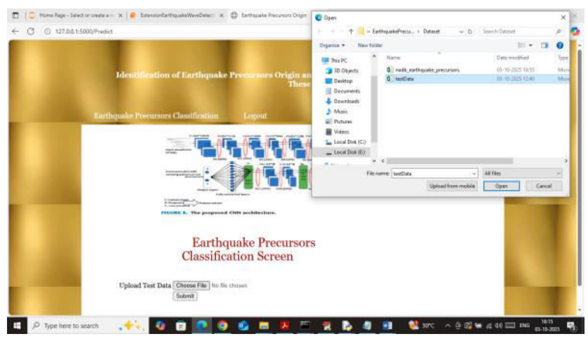

Fig 2:upload file

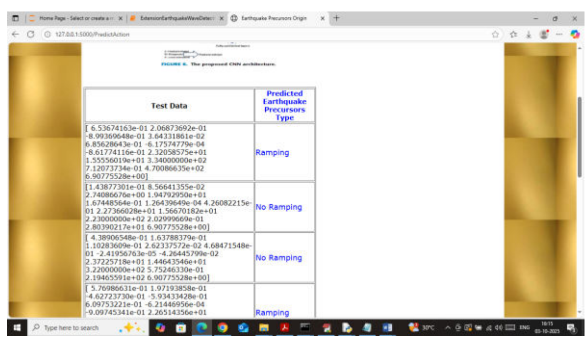

Fig 3:Predicted results

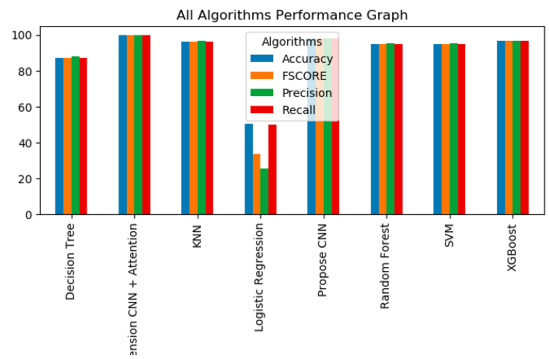

Fig 4:Accuracy Comaprision

5. CONCLUSION

Accurate identification and classification of earthquake precursors are essential for early warning and seismic mitigation. The study shown that the reliability of precursor analysis is increased when genuine ground-origin P-wave signals are separated from instrumental artifacts. By gathering and examining 429 data from the New Abu Dabbab station at various sample rates, the approach found ramping patterns associated with abnormal P-wave activity. Convolutional neural networks (CNNs) outperformed traditional machine learning techniques in signal classification, achieving 97.98% accuracy. Prediction accuracy increased to 99.81% when an attention mechanism was added to the CNN architecture. This demonstrates how attention-based deep learning models may highlight important seismic data pieces and capture complex temporal correlations for accurate real-time P-wave classification. The results demonstrate that contextual awareness and improved feature optimization may significantly reduce errors in seismic precursor identification. According to the study, deep learning combined with precise seismic monitoring might enhance risk mitigation strategies and early earthquake detection.

6. FUTURE SCOPE

More real-time seismic data from several monitoring stations in various areas might be added to the classification system. Prediction is improved by include antecedents such as temperature variations, gas emissions, and electromagnetic oscillations. False warnings would be reduced by more precise anomaly identification and signal denoising. To detect emergency circumstances more quickly, the system can be modified for real-time deployment and computational efficiency. Long-term reliability may be improved by using adaptive learning to update the model with new earthquake patterns. Enhancing alarm interfaces and visualization can expedite interpretation and decision-making during pre-seismic monitoring.

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Author Profiles

Ms. K. Baby Ramya is working as an Assistant Professor in the Department of MCA at SRK Institute of Technology, Enikepadu, Vijayawada, NTR District. She completed her MCA from Krishna University. She has nearly 3 years of teaching experience at SRK Institute of Technology. Her areas of interest include Machine Learning, Data Science, and Computer Applications.

Mrs. K. Pavani is working as an Assistant and Head of Department of MCA, in SRK Institute of technology in Vijayawada. She completed her MCA and M.Tech in Computer Science. She has 10 years of teaching experience in SRK Institute of technology, Enikepadu, Vijayawada, NTR District. Her areas of interest include AI and ML, etc.

Mr. A. Azees is an MCA student in the Department of Computer Applications at SRK Institute of Technology, Enikepadu, Vijayawada, NTR District. He completed his degree in B.Sc.(Computers and Physics) from SSR Degree College, Machilipatnam. His areas of interest are DBMS and Machine Learning.