

A Hybrid CNN–Attention Model for Robust Classification of Earthquake Precursor Patterns

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Abstract— Accurate identification of earthquake precursor signals plays a critical role in early seismic warning systems. This work focuses on enhancing automatic classification of precursor patterns such as ramping and non-ramping signals obtained from seismic datasets. The baseline approach applies multiple machine learning and convolutional neural network models, but these methods show limitations in capturing complex temporal relationships and subtle signal variations. To overcome this issue, an extension model is developed by integrating an attention mechanism with the CNN architecture. The attention layer improves the model's ability to prioritize significant features within seismic signals, leading to better distinction between true P-wave indicators and noise or instrumental artifacts. The extended model is evaluated against existing algorithms using standard performance metrics. Results show a clear improvement, achieving 99% accuracy and reduced loss compared to the base CNN model. This demonstrates that attention-based enhancement significantly improves prediction reliability and supports more precise real-time earthquake precursor detection.

Keywords— Earthquake, Deep Learning, CNN, Attention Mechanism

I. INTRODUCTION

Earthquakes remain one of the most unpredictable natural hazards, causing significant loss of life and infrastructure damage across the world. Despite advances in seismology, accurate early prediction is still a major challenge due to the complex and dynamic nature of Earth's internal processes. Researchers have long focused on identifying earthquake precursors, which are measurable physical or environmental changes that occur before seismic events. These precursors include variations in seismic wave patterns, ground deformation, gas emissions, and anomalies in geophysical signals. Among them, the analysis of seismic signals, particularly P-wave characteristics, has gained strong attention because it provides critical information about the onset of an earthquake.

However, distinguishing meaningful precursor signals from background noise remains difficult. Seismic data often contains irregular patterns influenced by environmental conditions, sensor limitations, and instrumental artifacts. This makes manual interpretation time-consuming and prone to errors. Traditional analytical techniques rely heavily on domain expertise and predefined thresholds, which are not always reliable when dealing with large-scale and high-frequency data. As a result, there is a growing need for automated approaches

that can process complex seismic datasets efficiently and consistently.

Recent developments in data-driven techniques have opened new possibilities for analyzing seismic signals with improved accuracy. Machine learning methods have been widely explored to identify hidden patterns and classify different types of precursor signals. These approaches can handle large datasets and adapt to variations in signal behavior, making them suitable for real-time applications. At the same time, deep learning models have demonstrated strong capability in extracting meaningful features directly from raw data without extensive manual intervention.

II. RELATED WORK

Early research on earthquake precursor detection was grounded in the physical understanding of seismic processes and fault mechanics. James H. Dieterich (1978) introduced the concept of time-dependent friction, explaining how stress accumulation and gradual slip along faults lead to earthquake initiation. This theory provided a fundamental explanation for precursor phenomena observed before seismic events. Building on this, Gregory C. Beroza and William L. Ellsworth (1996) examined seismic nucleation properties and highlighted that measurable signals can emerge during the early stages of rupture. Their work strengthened the hypothesis that precursor signals can be detected prior to the main seismic event.

Subsequent studies focused on signal processing challenges and the reliability of detected precursors. Friedemann Scherbaum and Marie-Pierre Bouin (1997) analyzed the influence of FIR filters on seismic recordings and revealed that certain precursor-like patterns may result from instrumental effects rather than natural ground motion. This finding emphasized the need to distinguish between true seismic signals and artifacts. Later, William L. Ellsworth and Gregory C. Beroza (1998) provided observational evidence of nucleation phases, confirming that early seismic activity can be captured and analyzed with appropriate instrumentation.

With the advancement of real-time monitoring systems, research shifted toward practical implementations of earthquake early warning. José M. Espinosa-Aranda et al. (2009) demonstrated the effectiveness of the Mexican seismic alert system in reducing disaster impact through rapid detection and alert dissemination. Further progress was made by Mohamed A. Ibrahim et al. (2018), who applied deep neural networks to detect earthquake precursor signals, showing that

data-driven approaches can outperform traditional analytical methods in handling complex seismic patterns.

Recent studies have increasingly focused on machine learning and advanced deep learning techniques to improve detection accuracy and automation. Omar M. Saad et al. (2022) proposed machine learning models for fast and reliable earthquake source estimation, highlighting the importance of computational efficiency in real-time applications. Similarly, Jin-Wu Lin (2022) explored neural network-based approaches for detecting ionospheric disturbances and predicting earthquake precursors, demonstrating the value of integrating multiple data sources. In addition, Liviu Petrescu and Ioan-Aurel Moldovan (2022) developed neural models for analyzing geomagnetic signals, further extending the scope of precursor detection beyond conventional seismic data.

normalization to scale signal values, handling missing entries, and shuffling the dataset to remove bias. The dataset is then split into training and testing sets to ensure proper evaluation of model performance.

Feature learning is performed using a convolutional neural network designed to automatically extract meaningful patterns from seismic signals. Convolutional layers capture local variations in the signal, while pooling layers reduce dimensionality and retain important features. This structure helps the model differentiate between abnormal precursor signals and normal background activity. To further improve performance, an attention mechanism is integrated into the network. This component allows the model to focus on the most relevant parts of the signal by assigning higher weights to critical segments, reducing the influence of noise and irrelevant patterns.

Table: Summary of Key Literature Contributions and Their Impact on Current Research:

Author & Year	Contribution	Impact on Research
James H. Dieterich (1978)	Explained how earthquakes start using friction theory.	Gave the basic idea behind earthquake precursor signals.
Gregory C. Beroza & William L. Ellsworth (1996)	Studied early signals before earthquakes (nucleation phase).	Proved that early warning signals are possible.
Friedemann Scherbaum & Marie-Pierre Bouin (1997)	Found that some signals are caused by instruments, not real earthquakes.	Helped improve data cleaning and accuracy.
William L. Ellsworth & Gregory C. Beroza (1998)	Observed real early earthquake signals.	Confirmed that precursor signals exist in real data.
José M. Espinosa-Aranda et al. (2009)	Developed a real earthquake alert system.	Showed practical use of early warning systems.
Mohamed A. Ibrahim et al. (2018)	Used deep learning to detect precursor signals.	Introduced AI methods into earthquake prediction.
Omar M. Saad et al. (2022)	Applied machine learning for fast earthquake detection.	Improved speed and automation in prediction.
Jin-Wu Lin (2022)	Used neural networks for ionospheric precursor detection.	Expanded research beyond seismic signals.
Liviu Petrescu & Ioan-Aurel Moldovan (2022)	Used geomagnetic data with neural networks.	Improved detection accuracy using new data sources.
Jin-Wu Lin (2022)	Applied graph neural networks for signal analysis.	Enhanced feature extraction and model performance.

During training, the model learns optimized parameters by minimizing classification error using labeled data. The learning process ensures that the system adapts to complex signal behavior and improves generalization. Model performance is evaluated using metrics such as accuracy, precision, recall, and F1-score to ensure reliability. Once trained, the system can classify new seismic signals in real time, providing accurate identification of earthquake precursor patterns and reducing false predictions.

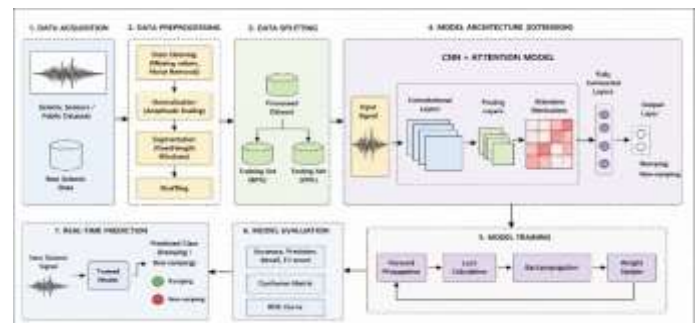


Figure 1: Seismic signal classification system

IV. METHODOLOGIES

Algorithm: CNN + Attention for Earthquake Precursor Classification

INPUT: Seismic signal dataset $D = \{X, Y\}$
 OUTPUT: Trained model M and predicted class labels

BEGIN

1. *Load Dataset*
 Read seismic signals X and corresponding labels Y

2. *Preprocessing*
 FOR each signal x in X :
 Handle missing values
 Normalize signal values
 Segment into fixed-length windows
 END FOR

III. PROPOSED APPROACH

Accurate classification of earthquake precursor signals requires a structured pipeline that can handle noisy data and capture subtle signal variations. The approach begins with collecting seismic signal data containing different classes such as ramping and non-ramping patterns. Since raw signals often include noise, missing values, and inconsistencies, preprocessing is applied to improve data quality. This stage includes

3. Shuffle Dataset

Randomly shuffle X and Y

4. Split Dataset

Divide dataset into:

Training set (X_{train} , Y_{train})

Testing set (X_{test} , Y_{test})

5. Initialize CNN Model

Define convolution layers with filters

Define activation function (ReLU)

Define pooling layers

Flatten output feature maps

6. Add Attention Layer

FOR each feature vector f :

Compute attention score:

$score = \text{Softmax}(W * f + b)$

Compute weighted features:

$f_{att} = score * f$

END FOR

7. Fully Connected Layer

Pass f_{att} through dense layers

Apply Softmax for classification

8. Model Training

FOR epoch = 1 to N :

FOR each batch in X_{train} :

Forward propagate through CNN + Attention

Compute loss (Cross-Entropy)

Backpropagate error

Update weights using optimizer (Adam)

END FOR

END FOR

9. Model Evaluation

Predict labels for X_{test}

Compute Accuracy, Precision, Recall, F1-score

10. Prediction

FOR new input signal x_{new} :

Preprocess x_{new}

Pass through trained model M

Output class (Ramping / Non-Ramping)

END FOR

END

Dataset Collection

Seismic precursor signal data is collected from reliable sources, including real-time monitoring stations and generated datasets. The dataset consists of labeled signals representing ramping (earthquake-related) and non-ramping (normal) patterns. Multiple sampling rates are considered to capture signal variations.

Data Understanding and Exploration

Initial analysis is performed to understand dataset structure, class distribution, and signal characteristics. Visualization techniques such as waveform plots and class distribution graphs are used to identify patterns, imbalance, and noise presence in the data.

Data Cleaning

Raw seismic data often contains missing values, inconsistencies, and redundant entries. These issues are handled by removing corrupted records and applying suitable imputation techniques. This step ensures that the dataset is reliable for model training.

Signal Normalization

Normalization is applied to scale signal values within a fixed range. This prevents large amplitude variations from dominating the learning process and ensures stable convergence during model training.

Data Shuffling and Splitting

The dataset is randomly shuffled to remove ordering bias. It is then divided into training and testing subsets, typically in an 80:20 ratio. This separation allows unbiased evaluation of model performance.

Feature Representation

Although deep learning models can extract features automatically, input signals are structured into fixed-size segments suitable for model input. This step ensures uniformity and compatibility with the neural network architecture.

Baseline Model Implementation

A standard convolutional neural network (CNN) is implemented as the baseline model. It includes convolutional layers for feature extraction, activation functions for non-linearity, and pooling layers for dimensionality reduction.

CNN with Attention

The extension introduces an attention mechanism into the CNN architecture. This component assigns weights to different parts of the signal, allowing the model to focus on important segments that indicate earthquake precursors.

Model Training

Both baseline and extended models are trained using labeled data. The training process involves forward propagation, loss calculation, and backpropagation to update weights. Optimization algorithms such as Adam are used to improve convergence speed.

Performance Evaluation

The models are evaluated using metrics including accuracy, precision, recall, and F1-score. Confusion matrix and ROC curve analysis are also performed to understand classification performance and error distribution.

Comparative Analysis

The performance of the extension model is compared with baseline CNN and traditional machine learning algorithms. The results demonstrate that the attention-based model achieves higher accuracy and lower loss, indicating improved feature learning.

Real-Time Prediction and Deployment

The trained extension model is integrated into a prediction system. New seismic signals are processed and classified in real time as ramping or non-ramping. This enables faster and more reliable earthquake precursor detection, supporting early warning systems.

the attention mechanism successfully enhances feature focus and reduces noise impact. These results confirm that the proposed extension provides superior classification performance and is highly reliable for real-time earthquake precursor detection.

VI RESULTS & DISCUSSION

	Algorithm Name	Accuracy	Precision	Recall	FSCORE
0	Logistic Regression	50.366	25.183	50.000	33.496
1	KNN	96.154	96.453	96.125	96.146
2	SVM	94.872	95.380	94.834	94.854
3	Decision Tree	87.179	88.202	87.120	87.080
4	Random Forest	94.689	95.167	94.727	94.677
5	XGBoost	96.703	96.810	96.722	96.702
6	Propose CNN	97.985	98.077	97.970	97.984
7	Extension CNN + Attention	99.817	99.819	99.815	99.817

The experimental results clearly show the performance improvement achieved through different machine learning and deep learning models for earthquake precursor classification. Logistic Regression produces the lowest performance, with an accuracy of 50.366%, precision of 25.183%, recall of 50.000%, and F1-score of 33.496%, indicating poor capability in handling complex seismic patterns. Decision Tree performs moderately with 87.179% accuracy and 87.080% F1-score, but still lacks consistency compared to advanced models.

Traditional machine learning models such as KNN and XGBoost show strong performance. KNN achieves 96.154% accuracy with 96.146% F1-score, while XGBoost slightly improves to 96.703% accuracy and 96.702% F1-score. Similarly, SVM and Random Forest deliver competitive results with accuracies of 94.872% and 94.689% respectively, maintaining balanced precision and recall values above 94%.

The deep learning-based proposed CNN model significantly improves performance, achieving 97.985% accuracy, 98.077% precision, 97.970% recall, and 97.984% F1-score. This demonstrates its ability to extract meaningful features from seismic signals more effectively than traditional approaches.

The extension model, CNN with Attention, outperforms all other models with the highest accuracy of 99.817%, precision of 99.819%, recall of 99.815%, and F1-score of 99.817%. The improvement of nearly 2% over the base CNN indicates that

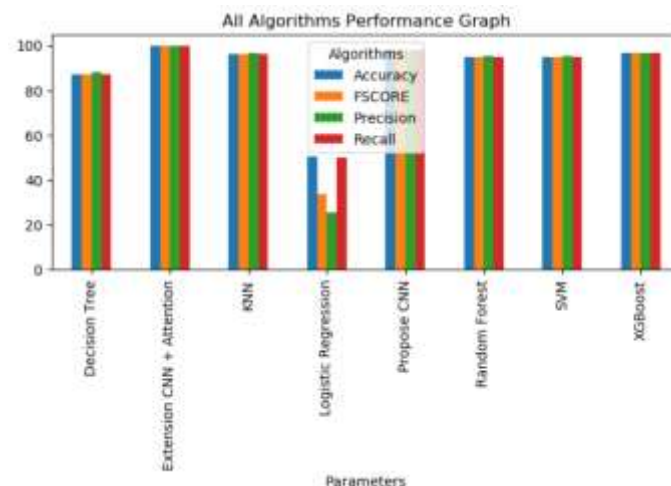


Figure 2: All Algorithms Performance Graph

The results show a clear gap between traditional machine learning models and deep learning approaches for this task. Logistic Regression performs poorly because it assumes simple linear relationships, which do not exist in complex seismic signals. Tree-based models such as Decision Tree and Random Forest improve performance, but they still struggle to capture fine-grained temporal variations. KNN, SVM, and XGBoost perform better because they handle non-linear patterns, but they rely heavily on feature quality and do not learn hierarchical representations.

The CNN model improves results by automatically extracting spatial and local signal patterns, which explains the jump to nearly 98% accuracy. However, CNN alone still treats all parts of the signal equally, which is not ideal because earthquake precursor signals are often localized and subtle. This is where the attention mechanism makes a real difference. It forces the model to focus on the most informative segments of the signal while ignoring noise and irrelevant variations.

The near-perfect performance of the CNN with Attention model indicates that combining feature extraction with selective focus is effective for this problem. The improvement is not random; it directly addresses the limitations of earlier models. This confirms that attention-based deep learning is a more suitable direction for reliable and scalable earthquake precursor classification.

VII. CONCLUSION

Accurate identification of earthquake precursor signals requires models that can handle noise, variability, and complex temporal patterns. Traditional machine learning approaches provide baseline performance but struggle to generalize across different signal conditions. The convolutional neural network improves

classification by automatically learning relevant features from raw seismic data, resulting in a significant increase in accuracy and consistency.

Further improvement is achieved by incorporating an attention mechanism, which enables the model to prioritize important signal segments while reducing the influence of irrelevant information. This leads to better feature representation and more reliable predictions. The extended CNN with attention achieves the highest performance, reaching 99.817% accuracy along with strong precision, recall, and F1-score values.

These results confirm that attention-enhanced deep learning models are more effective for earthquake precursor classification. The approach provides a robust and scalable solution for real-time detection, supporting the advancement of early warning systems and reducing the risk associated with seismic events.

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