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Automated Artificial Intelligence Approach for Reliable Earthquake Precursors Detection and Classification Using Hybrid Deep Learning Models

K Yatheendra[1], M Siva Priya[2], Jithendra Kukutla[3]

[1]Assistant Professor, Department of CSE(AI & ML),, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, E-mail: k.yatheendra84@gmail.com, ORC-ID: https://orcid.org/0009-0003-1382-8587

[2]P.G Scholar, Department of MCA, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, E-mail:sivapriyapriya757@gmail.com, ORC-ID: https://orcid.org/0009-0008-1683-0697

[3]Assistant Professor, Department of CSE(AI &ML), Santhiram Engineering College, Nandyal, Kurnool Dist. AP, E-mail:24x51d1304@srecnandyal.edu.in

Abstract: The precise detection of earthquake precursors before P-wave arrival is essential for advancing real-time seismic monitoring and refining earthquake source parameter estimation. Traditional P-wave detection methods frequently encounter ambiguity stemming from the simultaneous presence of instrumental artifacts and natural ground-origin precursory signals, leading to misclassification and timing discrepancies. An automated artificial intelligence system has been designed to reliably classify precursory signal patterns, thereby overcoming these constraints. The analysis utilizes a synthetically constructed dataset that mirrors the properties of precursor patterns seen in seismic recordings obtained at various sampling rates. Dataset exploration and visualization are conducted by trend strength distributions and correlation analysis, succeeded by preprocessing and an 80:20 train-test division. Various classification models are employed, including Logistic Regression, K-Nearest Neighbors, Support Vector Machine, Decision Tree, Random Forest, Naive Bayes, XGBoost, Voting Classifier, and convolutional neural networks, utilizing diverse data splits, in addition to sophisticated hybrid Stacking and BiLSTM architectures. The evaluation of model performance is conducted by accuracy, precision, recall, F1-score, and ROC-AUC metrics, supplemented by comparison performance graphs. The BiLSTM model demonstrates superior performance across all assessed methodologies, with an accuracy of 99.8% and an almost flawless ROC-AUC, markedly exceeding the results of baseline and ensemble models. Explainable AI methodologies utilizing LIME and SHAP facilitate the interpretation of feature contributions, while their integration with a Flask-based framework allows for real-time user input, preprocessing, prediction, and result visualization, thus enhancing automated precursor classification and P-wave arrival determination.

***"Index Terms:** Precursory segments, seismic nucleation phase, nano seismology, FIR effect, machine learning (ML), deep learning, convolutional neural network (CNN)".*

1. INTRODUCTION

Precursory signals of earthquakes that manifest before the arrival of P-waves have garnered significant interest for their potential to enhance earthquake early warning and source characterisation systems. These precursors may arise from several physical causes, including geomagnetic disturbances, seismic nucleation processes, nanoscale seismicity, gas emissions, and hydrological changes, typically linked to natural terrestrial occurrences [1], [2]. These signals are generally feeble, ephemeral, and markedly varied, yet they convey significant information regarding the preparatory period of fault rupture. Simultaneously, contemporary seismic acquisition technologies may produce instrumental artifacts that resemble authentic precursory activity, so confounding the analysis of recorded waveforms [3].

A significant obstacle stems from the difficulty in accurately differentiating genuine ground-based antecedents from instrumental artifacts seen in seismic records. Instrumental effects, like oscillating patterns generated during digitization, may manifest just prior to abrupt P-wave arrivals and could be erroneously regarded as physical predecessors [4]. This ambiguity directly influences the selection of P-wave beginning times, as analysts and automated systems may identify arrival times either before to or after to the precursor segment [5]. Variability in onset determination leads to inaccuracies in estimating earthquake parameters, such as origin time, magnitude, and fault features, especially in automated processes employed by earthquake early warning systems [6]. Previous studies have investigated restricted types of precursor patterns; however, current methodologies frequently depend on tiny datasets or concentrate on a singular precursor type, resulting in a deficiency in thorough characterization and categorization [7].

The main aim of this study is to examine the source of precursory signal patterns detected prior to P-wave arrivals and to create a systematic framework for distinguishing between natural ground-based and instrumental predecessors. The study seeks to enhance the consistency and reliability of P-wave onset assessment by analyzing a diverse array of precursor morphologies, elucidating whether the arrival should be recognized before to or after to the precursor segment. The approach aims to facilitate automatic precursor recognition compatible with current seismic monitoring systems, thus minimizing subjective interpretation and improving consistency across datasets collected under diverse settings [8].

This contribution is significant due to its potential to enhance the robustness and accuracy of earthquake early warning systems, which rely fundamentally on precise and timely P-wave detection [9]. The proposed approach can improve real-time hazard assessment and subsequent decision-making by diminishing uncertainty in onset timing and alleviating mistakes from misclassified precursors. Enhanced precursor categorization ultimately facilitates more accurate size estimation, fault mechanism investigation, and warning distribution, hence bolstering risk reduction initiatives in seismically active areas globally [10].

2. LITERATURE REVIEW

Prior research has examined diverse types of earthquake precursors and their possible contribution to enhancing seismic monitoring. Lin [11] illustrated the efficacy of spectral-based learning in detecting abnormalities in ionospheric total electron content prior to a significant earthquake, underscoring the viability of recognizing non-seismic precursors through sophisticated data-driven techniques. Previous seismological research conducted by Beroza and Ellsworth [12] and Ellsworth and Beroza [13] provide essential insights into seismic nucleation stages, demonstrating that earthquakes are preceded by modest rupture processes detectable under optimal conditions. These studies established the physical foundation of natural ground-based precursors while also highlighting their low amplitudes and restricted detectability within standard seismic networks.

Concurrently, other research examined instrumental effects that can produce signals akin to physical antecedents. Scherbaum and Bouin [14] examined the effects of finite impulse response filtering on seismic recordings and shown that non-causal filter behavior may generate rhythmic patterns preceding impulsive P-wave arrivals. Samy [15] further analyzed contemporary signal processing methodologies for the extraction of earthquake information, observing that artifacts associated with digitization can substantially affect onset identification. Although these contributions elucidated the origins of certain instrumental antecedents, they predominantly concentrated on discrete signal types and failed to offer systematic methodologies for distinguishing between instrumental and natural sources across varied datasets.

As the focus on real-time applications intensifies, machine learning has been progressively utilized in earthquake early warning systems. Saad et al. [16] established that learning-based methodologies may swiftly and accurately ascertain earthquake source sites, providing distinct benefits in terms of speed and scalability compared to conventional methods. Tajima and Hayashida [17] examined the operational significance of early warning time improvements, highlighting the responsiveness of warning efficacy to precise P-wave arrival detection. While these research underscored the potential of data-driven methodologies in operational systems, they predominantly presupposed dependable phase selecting and did not clearly confront the ambiguity caused by precursory signal segments.

Operational earthquake early warning systems exemplify advancements as well as ongoing problems. Böse et al. [18] introduced the CISN ShakeAlert system as a thorough illustration of regional early warning, whereas Espinosa-Aranda et al. [19] and Hoshiba et al. [20] chronicled the development of national warning systems in Mexico and Japan, respectively. These systems demonstrate societal relevance and technical viability; however, their performance may be compromised by inaccuracies in automatic phase choosing, especially when anomalous waveform characteristics precede P-wave onsets.

Previous research has enhanced comprehension of antecedent phenomena, instrumental artifacts, and early warning system design; nonetheless, significant gaps persist. Current research frequently examines physical or instrumental antecedents separately, depends on restricted datasets, or lacks automated methods to differentiate between the

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origins of precursors. This gap inspires the current contribution, which seeks to amalgamate precursor origin analysis with automated categorization for inclusion into real-time seismic monitoring. The suggested approach aims to improve the resilience and reliability of earthquake early warning and source parameter estimate systems by resolving ambiguity in P-wave onset identification caused by precursors.

3. MATERIALS AND METHODS

The suggested system aims to autonomously categorize earthquake precursory signal patterns that occur before P-wave arrival, with the goal of enhancing real-time seismic phase identification and minimizing arrival-time uncertainty. A synthetically generated dataset is employed to replicate the statistical, temporal, and spectral properties of precursory seismic waves captured at various sampling rates. The comprehensive approach adheres to a systematic learning pipeline encompassing data ingestion, exploratory analysis, normalization, and supervised model training and validation. A variety of classification methods is utilized to capture both linear and non-linear signal features, augmented by ensemble procedures that improve generalization through the use of complementary decision-making behaviors. A bidirectional recurrent architecture is utilized to enhance the discrimination of complex temporal patterns by modeling sequential dependencies in precursor signals. Model interpretability is enhanced by explainable artificial intelligence techniques, facilitating transparent evaluation of feature contributions and bolstering faith in automated decisions. Ultimately, integration inside a streamlined web-based framework facilitates real-time engagement, forecasting, and visualization, hence endorsing scalable deployment. The system collectively improves resilience, accuracy, and reliability in automated precursor categorization and P-wave arrival detection.

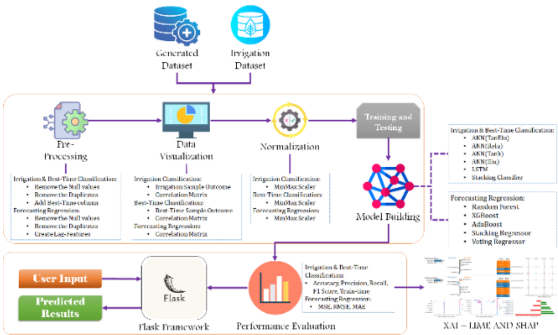

Fig.1 Proposed Architecture

This system design depicts a comprehensive machine learning pipeline, commencing with dataset ingestion and visualization for trend analysis and correlation insights. The data is divided into training and testing sets to develop several models, including Random Forest, Decision Tree, Logistic Regression, KNN, XGBoost, Naïve Bayes, and SVM. An ensemble voting classifier improves predictive performance. Model evaluation employs accuracy, precision, recall, and F1-score. Explainable AI utilizing LIME and SHAP guarantees transparency, while a Flask-based interface facilitates the deployment of the optimal model for real-time predictions.

a) Dataset Collection:

This study utilizes a synthetically generated seismic precursor dataset sourced from a publicly accessible resource. The dataset comprises 6,000 samples characterized by 14 descriptive features that encapsulate statistical, temporal, and spectral signal attributes, including moments, energy, entropy, peak-related metrics, and sampling rate. Each sample is categorized into two classes: natural ground-based precursors and instrumental artifacts. The dataset is entirely balanced, controlled for noise, and constructed across several sample rates, rendering it highly suitable for rigorous assessment of automated precursor classification and real-time seismic phase identification.

	mean	std	skewness	kurtosis	rms	slope	trend_strength	spectral_centroid	spectral_bandwidth	n_peaks	mean_peak_height	energy	entropy	sampling_rate	label
0	0.324296	0.237175	0.960679	-0.074088	0.401771	0.000755	0.919380	8.333021	7.731177	318	0.366637	161.419716	6.907755	50	1
1	0.315052	0.224341	0.946076	-0.087694	0.386764	0.000714	0.918377	37.331975	33.471833	332	0.361574	149.586774	6.907755	200	1
2	0.332525	0.224804	0.951482	-0.050303	0.401385	0.000716	0.919621	17.455386	15.914374	325	0.378909	161.109611	6.907755	100	1
3	0.332563	0.238011	0.931687	-0.131008	0.408959	0.000761	0.922397	17.598917	16.437764	322	0.372649	167.247616	6.907755	100	1
4	0.344519	0.236490	0.949669	-0.103026	0.417877	0.000753	0.918870	9.474980	8.226879	320	0.380445	174.620982	6.907755	50	1

Fig.2 precursor_patterns Dataset

b) Pre-Processing:

The preprocessing phase organizes seismic precursor data via exploratory analysis, feature enhancement, stratified data segmentation, and evaluation configuration, guaranteeing dependable learning, minimized redundancy, and thorough performance evaluation for automatic classification.

Exploratory Data Analysis and Visualization: Exploratory data analysis is conducted to comprehend the statistical characteristics and distinguishability of precursory signal attributes among various groups. The examination of feature-wise distribution reveals differences in essential characteristics like slope and trend intensity, facilitating visual comparison among precursor groups. Correlation analysis is utilized to investigate inter-feature connections and redundancy. This stage is crucial for understanding feature significance, recognizing distinguishing patterns, and facilitating educated preprocessing and modeling choices.

Feature Selection and Reduction: Feature selection is utilized to enhance the input representation by eliminating attributes that may cause repetition or possess minimal discriminative value. Eliminating highly correlated or less useful features aids in reducing dimensionality and alleviating overfitting, while maintaining the most pertinent statistical and spectral attributes of the signals. This phase improves model efficiency and stability by streamlining the feature space, enhancing generalization ability, and ensuring that classification decisions are based on significant signal descriptors.

Data Partitioning and Stratified Sampling: The dataset is partitioned into training and testing subsets utilizing a predetermined ratio, while maintaining the original class distribution. Stratified sampling guarantees that both subsets retain representative samples from each predecessor group, hence avoiding class bias in model training and assessment. This stage is essential for acquiring impartial performance evaluations, facilitating equitable comparisons among classifiers, and guaranteeing that trained models generalize proficiently to novel data.

Evaluation Metric Preparation: A systematic evaluation framework is created by delineating various complementing performance indicators to evaluate categorization efficacy. Metrics including accuracy, precision, recall, F1-score, and area under the ROC curve are designed to evaluate many facets of model performance, encompassing correctness, robustness, and class-specific discrimination. This stage guarantees uniform and thorough performance evaluation among all classifiers, facilitating objective comparison and dependable validation of the proposed system.

c) Algorithms:

Random Forest: Random Forest operates as an ensemble classifier that consolidates decisions from numerous tree models to improve robustness and diminish variation. By encompassing varied feature interactions, it enhances generalization and ensures consistent performance in the presence of noisy and nonlinear data situations.

Decision Tree: Decision Tree models classify decisions using hierarchical, feature-based rules. It presents clear decision logic, effectively captures nonlinear relationships, and facilitates rapid training and inference, rendering it advantageous for interpretability and baseline performance evaluation.

Naive Bayes: Naive Bayes functions as a probabilistic classifier that allocates class labels according to assessed feature probabilities. Its simplicity facilitates rapid learning and inference, while ensuring dependable performance in high-dimensional spaces and functioning as an efficient baseline model.

Logistic Regression: Logistic Regression calculates class probabilities through linear decision limits. It provides consistent and interpretable predictions, exhibits robust generalization with regularization, and functions as a dependable baseline for evaluating more intricate classification methods.

K-Nearest Neighbors: K-Nearest Neighbors conducts classification by assessing similarity to adjacent samples within the feature space. It adjusts to local data structures without explicit model assumptions, successfully delineating nonlinear class borders and representing inherent data distribution.

Support Vector Machine: Support Vector Machine establishes ideal dividing margins between classes to enhance discrimination. It adeptly manages high-dimensional feature spaces, facilitates nonlinear separation, and provides robust generalization performance in intricate classification contexts.

XGBoost: XGBoost employs gradient-boosted decision trees to progressively enhance classification precision. By prioritizing misclassified data and integrating regularization, it attains substantial predictive accuracy, scalability, and resilience to overfitting.

Voting Classifier: The Voting Classifier amalgamates predictions from various heterogeneous classifiers to improve decision reliability. By utilizing the strengths of complementary models, it diminishes bias and variance, leading to more consistent and stable classification results.

CNN (60% Training Split): The Convolutional Neural Network, trained on limited data, assesses feature learning performance under restricted conditions. It captures hierarchical signal representations while evaluating generalization performance in scenarios with few training samples.

CNN (80% Training Split): The Convolutional Neural Network, utilizing an 80% training split, effectively balances feature extraction and validation accuracy. This arrangement facilitates steady representation learning and allows for equitable performance comparison with alternative categorization methods.

CNN (95% Training Split): The Convolutional Neural Network with a 95% training split underscores rigorous feature extraction. It enables the assessment of learning capacity and overfitting tendencies when validation data is scarce.

Stacking Classifier (Decision Tree and Random Forest): The Stacking Classifier amalgamates results from Decision Tree and Random Forest using a hierarchical ensemble approach. By acquiring optimal combinations of foundational predictions, it enhances robustness, accuracy, and generalization across varied data patterns.

BiLSTM: Bidirectional Long Short-Term Memory (Bi-LSTM) captures temporal dependencies by processing sequences in both forward and reverse orientations. It improves classification accuracy by understanding long-range contextual links in sequential data representations.

d) Integration of XAI & Flask Framework:

The incorporation of Explainable Artificial Intelligence improves transparency by offering both local and global interpretability of classification judgments. LIME elucidates individual predictions by pinpointing the most significant features affecting class assignment, whereas SHAP offers an extensive perspective on feature influence across several samples. These strategies facilitate the lucid understanding of intricate model behavior, enhancing user trust and aiding in the validation of automated judgments.

The Flask framework facilitates the efficient deployment of trained models and explainability modules in an interactive setting. It facilitates real-time user input, automated preprocessing, prediction generation, and presentation of categorization outcomes with accompanying explanatory insights. This integration enables scalable, user-friendly access to model predictions and interpretability outputs, fostering practical implementation in real-time seismic monitoring systems.

4. EXPERIMENTAL RESULTS

Accuracy: The accuracy of a test refers to its capacity to correctly distinguish between patient and healthy cases. To assess the accuracy of a test, one must compute the ratio of true positives and true negatives across all assessed cases. This can be expressed mathematically as:

$$Accuracy = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} (1)$$

Precision: Precision assesses the proportion of accurately classified cases among those identified as positive. Consequently, the formula for calculating precision is expressed as:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} (2)$$

Recall: Recall is a metric in machine learning that assesses a model's capacity to recognize all pertinent instances of a specific class. It is the ratio of accurately predicted positive observations to the total actual positives, offering insights into a model's efficacy in identifying occurrences of a specific class.

$$Recall = \frac{\text{TP}}{\text{TP } + \text{ FN}} (3)$$

F1-Score: The F1 score is a metric for evaluating the accuracy of a machine learning model. It integrates the precision and recall metrics of a model. The accuracy metric quantifies the frequency of true predictions generated by a model throughout the entire dataset.

$$F1\ Score = 2 * \frac{Recall \text{ X } Precision}{Recall + Precision} * 100(1)$$

AUC-ROC Curve: The AUC-ROC Curve is a metric for evaluating classification performance across different threshold levels. ROC plots the True Positive Rate versus the False Positive Rate. The AUC measures the model's overall capacity to differentiate across classes, with a higher AUC signifying superior model performance.

$$AUC = \sum_{i=1}^{n-1} (FPR_{i+1} - FPR_i) \cdot \frac{TPR_{i+1} + TPR_i}{2} \qquad (5)$$

Table.1 Performance Evaluation Table

ML Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
RandomForest	0.976	0.976	0.976	0.976	0.974
Decision Tree	0.988	0.988	0.988	0.988	0.990
Logistic Regression	0.948	0.956	0.948	0.949	0.996
KNN	0.974	0.976	0.974	0.974	0.995
XGBoost	0.978	0.978	0.978	0.977	1.000
Naive Bayes	0.926	0.941	0.926	0.928	0.997

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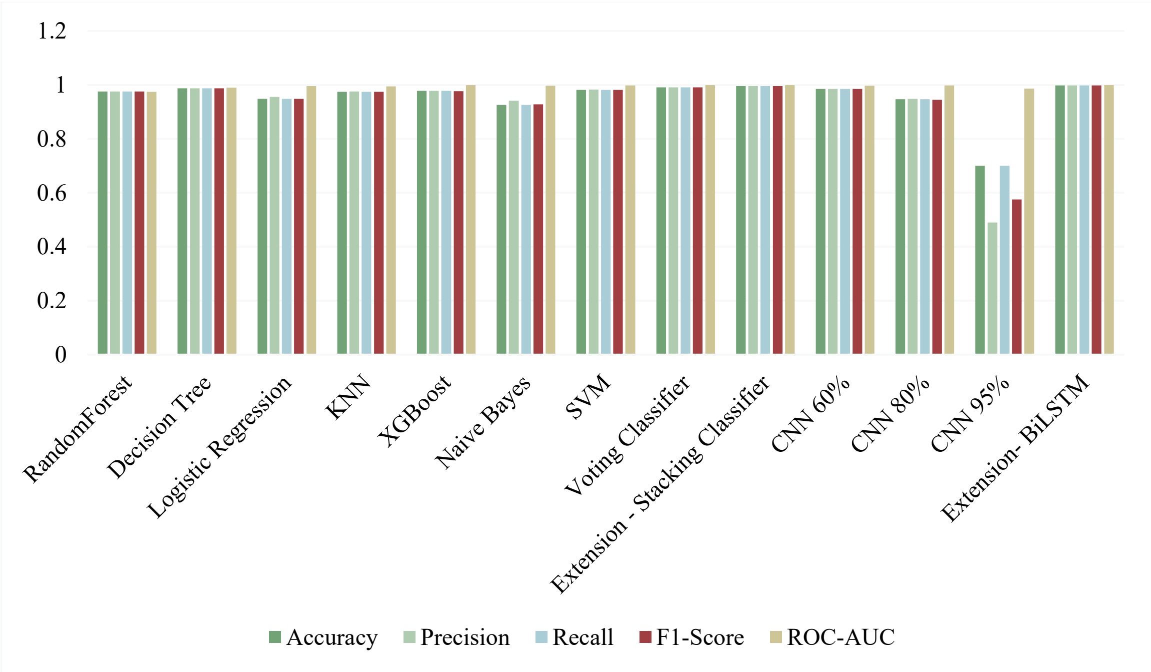
SVM	0.982	0.983	0.982	0.982	0.998
Voting Classifier	0.991	0.991	0.991	0.991	1.000
Extension - Stacking Classifier	0.996	0.996	0.996	0.996	1.000
CNN 60%	0.985	0.985	0.985	0.985	0.997
CNN 80%	0.947	0.949	0.947	0.945	0.998
CNN 95%	0.700	0.490	0.700	0.576	0.986
Extension- BiLSTM	**0.998**	**0.998**	**0.998**	**0.998**	**1.000**

The performance evaluation table contrasts several machine learning and deep learning models, indicating that ensemble and deep models, particularly BiLSTM and stacking classifiers, attain enhanced accuracy, robustness, and optimal ROC-AUC scores.

Graph.1 Comparison Graph



The comparative graph illustrates performance metrics for models, emphasizing constantly elevated accuracy and ROC-AUC for ensemble and BiLSTM methodologies, whereas CNN exhibits diminished performance at greater splits.

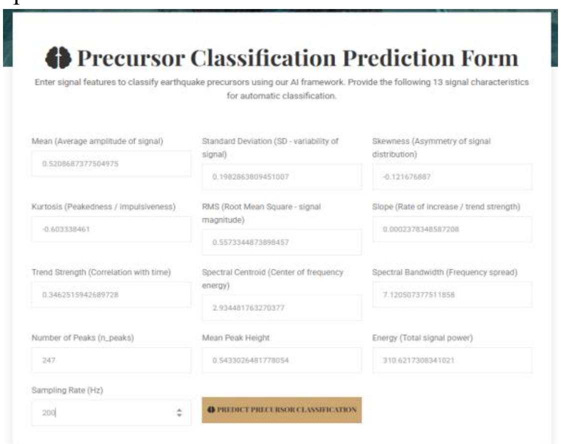


Fig.3 Enter the input data

The image depicts a Precursor Classification Prediction Form in which users provide signal parameters such as mean, RMS, skewness, peaks, and energy to facilitate the automatic classification of earthquake precursors via an AI model.

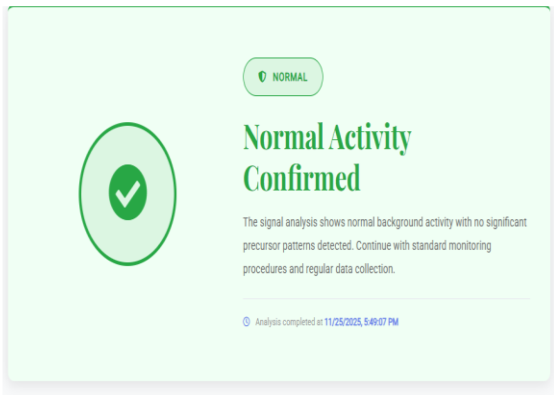


Fig.4 Predicted Result

The graphic presents a "Normal Activity Confirmed" result, signifying that signal analysis identified solely typical background activity without notable antecedent patterns, advising ongoing monitoring and standard data collecting.

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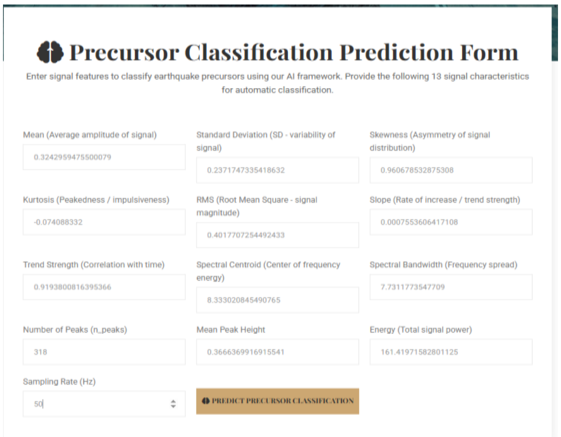

Fig.5 Enter the input data

The graphic displays a Precursor Classification Prediction Form that inputs extracted signal data, including kurtosis, RMS, spectral properties, peaks, and energy, to forecast earthquake precursor activity with an AI-based model.

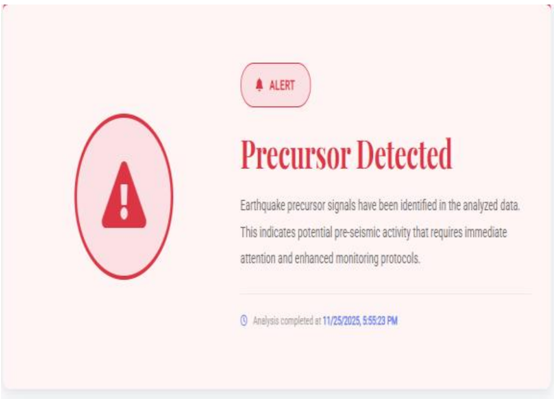

Fig.6 Predicted Result

The graphic shows a "Precursor Detected" notice, showing discovered earthquake precursor signals that signify potential pre-seismic activity, necessitating rapid attention, increased monitoring, and precautionary measures.

5. CONCLUSION

This technique is designed to accomplish precise and automated categorization of earthquake precursory signal patterns prior to P-wave arrival, aiming to enhance real-time seismic phase identification and diminish arrival-time uncertainty. The framework utilizes a synthetically produced dataset intended to encapsulate the statistical and spectral properties of precursory seismic events documented at various sampling rates. A wide array of classification models is employed, encompassing Logistic Regression, K-Nearest Neighbors, Support Vector Machine, Decision Tree, Random Forest, Naive Bayes, XGBoost, Voting Classifier, and Convolutional Neural Networks, utilizing various data split configurations, in addition to sophisticated hybrid Stacking and BiLSTM architectures. Performance evaluation employs accuracy, precision, recall, F1-score, and ROC-AUC measures to guarantee objective and valid comparisons among all models. The BiLSTM model attains superior performance, with an accuracy of 99.8%, thereby illustrating the efficacy of sequential learning in precursory signal categorization. To improve transparency and reliability, explainable artificial intelligence methods like LIME and SHAP are employed to elucidate feature-level contributions in model predictions. Moreover, integration with a Flask-based framework facilitates real-time user input, automated preprocessing, model inference, and result visualization. The system provides a robust, interpretable, and deployable solution that enhances automated earthquake precursor analysis and facilitates dependable seismic decision-making. The future potential of this system is enhancing validation through the utilization of extensive real-time seismic datasets obtained from various geographic areas to further evaluate generalization and robustness. Integration with continuous seismic monitoring networks can facilitate early-warning assistance and adaptive thresholding for fluctuating signal conditions. Advanced deep learning architectures and attention-based temporal models may further improve precursor discrimination. Integrating supplementary explainability methods can enhance transparency for domain specialists, while enhancing computational efficiency will facilitate low-latency implementation. Ultimately, seamless integration with operational seismic observatories can promote wider adoption of automated earthquake monitoring and decision-support systems.

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