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Research Paper**MACHINE LEARNING FOR FAST AND RELIABLE SOURCE-LOCATION ESTIMATION IN EARTHQUAKE EARLY WARNING****Devarala Siva Nagaraju *1, P. Adhi lakshmi*2**

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ABSTRACT

This project presents a machine learning-based approach for rapid and accurate earthquake source-location estimation to enhance the efficiency of Earthquake Early Warning (EEW) systems. A Random Forest (RF) model is developed to predict earthquake epicenters using differential P-wave arrival times recorded at the first five seismic stations relative to a reference station. These arrival time differences, combined with the corresponding station coordinates, serve as input features to the RF model. The model is trained and evaluated using an earthquake catalog from Japan. Experimental results show that the RF model achieves a high location prediction accuracy with a Mean Absolute Error (MAE) of 2.88 km. Remarkably, the model maintains reliable performance even when trained on just 10% of the dataset or using data from as few as three seismic stations ($MAE < 5$ km). The proposed system is efficient, generalizable, and robust, making it a valuable addition to real-time EEW systems for fast and dependable earthquake source localization.

Keywords: Earthquake Early Warning (EEW), Machine Learning, Random Forest, Epicenter Estimation, P-wave Arrival Time, Seismic Data, Source Localization.

1.INTRODUCTION

Earthquakes are some of the most catastrophic natural disasters, capable of causing significant human casualties, property damage, and long-term socio-economic consequences. Because of the sudden and unpredictable nature of earthquakes, the implementation of **Earthquake Early Warning (EEW)** systems has become crucial. EEW systems are designed to provide alerts

within seconds after a seismic event is detected, allowing people and systems to take protective actions before the strong shaking arrives. A key function of an EEW system is the rapid and accurate estimation of an earthquake's location, particularly the epicenter. Traditional methods for determining epicenters use iterative least-

squares inversion techniques that rely on arrival times from many stations. These methods, although effective in static analyses, can be slow, computation-intensive, and sensitive to the accuracy of input data, such as noise or time synchronization issues. In a real-time setting, any delay in estimating the location of an earthquake could reduce the effectiveness of the warning system.

Recent advancements in machine learning (ML) have introduced new ways to solve complex problems in seismology. ML models are capable of learning nonlinear relationships from data and making predictions faster than traditional algorithms. Random Forests (RF), in particular, are ensemble learning models that combine multiple decision trees to produce high-performing, robust predictions. They are

well-suited for classification and regression tasks involving noisy, incomplete, or variable-quality data, making them an excellent choice for real-time seismic applications.

This project proposes the use of a machine learning approach to improve the speed and reliability of earthquake epicenter estimation. Specifically, we develop a Random Forest model that estimates the location of an earthquake using only the first five P-wave arrival times at nearby seismic stations. Instead of relying on absolute arrival times, we calculate the time difference between these arrivals relative to the first station that detects the event. These time differences, along with the locations of the recording stations, are used as inputs to the model.

The aim is to reduce the latency and data dependency typically required by traditional location algorithms. We also evaluate how well the model performs when trained with limited data or when using as few as three recording stations. By achieving accurate results under such conditions, the system can contribute significantly to real-time EEW performance.

Proposed Approach

The core of the system is a Random Forest regression model, trained on historical earthquake data collected from Japan. Each data sample consists of:

The differential P-wave arrival times at up to five stations.

The geographic coordinates of those stations. The true epicenter coordinates, which serve as the labels for supervised learning. The use of differential arrival times, rather than absolute ones, adds robustness to the model by reducing dependence on perfect time synchronization across stations. After the model is trained, it can quickly and accurately estimate the location of new seismic events within seconds after detection by just a few stations, thus supporting faster alert generation.

Integrating machine learning into EEW systems provides several notable advantages. First, the prediction time is extremely low, as the trained model can make instant inferences once it receives input data. Second, the system can work effectively with limited station data, which is essential in the early seconds of an earthquake when only a few stations may have recorded the event. Third, the model is generalizable and can be retrained for deployment in other regions with different geological features.

In addition to EEW, the methodology can be extended to aftershock detection, localized seismic risk monitoring, and real-time disaster response coordination. It also demonstrates how data-driven models can complement physics-based approaches in seismology, offering faster and often more adaptable solutions.

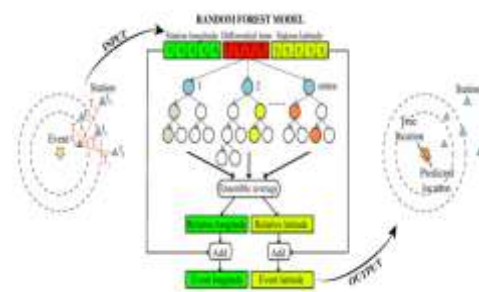
The rest of this project report is organized as follows:

Section 2 presents a review of existing literature and approaches used in earthquake location and machine learning applications in seismology.

Section 3 discusses the dataset used, feature engineering, and training of the Random Forest model.

Section 4 details the results, performance evaluation, and comparison between different model configurations.

Section 5 concludes the study and outlines future directions for research and development.



2. METHODOLOGY

To develop a fast and reliable earthquake source-location estimation system, this project applies a machine learning approach using the Random Forest (RF) regression

model. The main goal is to estimate the epicenter coordinates of an earthquake in near-real time using only a few early seismic signals. The methodology begins with the collection and preparation of a historical earthquake dataset obtained from seismic networks in Japan. Each record in the dataset includes the earthquake's actual epicenter coordinates and the corresponding P-wave arrival times at various seismic stations, along with the geographic coordinates of those stations.

For each seismic event, we identify the first five stations that recorded the P-wave. Among these, the station that first detects the signal is designated as the reference station. To minimize the impact of clock errors and timing inconsistencies across different stations, we compute differential P-wave arrival times. This means that for each of the remaining four stations, we calculate the arrival time difference relative to the reference station. If t_{i_i} denotes the arrival time at station i_i and t_{ref} is the arrival time at the reference station, then the differential arrival time Δt_i is defined as:

This method eliminates the need for absolute synchronization and allows the model to generalize better across diverse conditions. The next step involves constructing the input vector for the Random Forest model. This input vector combines the geographical coordinates of all five stations, (x_i, y_i) , along with the differential arrival times for the non-reference stations. The complete input for a sample looks like this:

$$\Delta t_i = t_i - t_{ref}$$

The output of the model is a two-dimensional vector representing the true epicenter location, given by:

$$Y = [x_e, y_e]$$

The Random Forest model used here is an ensemble of decision trees, each trained on a different subset of the data. During

prediction, each tree makes an independent estimate of the epicenter, and the final prediction is the average of these estimates. Mathematically, if there are T trees in the forest, the predicted epicenter $\hat{Y}$ is:

$$\hat{Y} = \frac{1}{T} \sum_{i=1}^T f_i(X)$$

where $f_i(X)$ is the prediction made by the i -th tree.

For training the model, we split the data into training and testing subsets. We use the Mean Squared Error (MSE) as the loss function to train the model. The MSE is defined as:

$$MSE = \frac{1}{N} \sum_{j=1}^N [(x_{ej} - \hat{x}_j)^2 + (y_{ej} - \hat{y}_j)^2]$$

Here, (x_{ej}, y_{ej}) represents the actual epicenter of the j -th event, while $(\hat{x}_j, \hat{y}_j)$ is the predicted location, and N is the total number of samples in the test set. To better interpret the model's performance, especially in real-world distances, we also calculate the Mean Absolute Error (MAE) in kilometers:

$$MAE = \frac{1}{N} \sum_{j=1}^N \sqrt{(x_{ej} - \hat{x}_j)^2 + (y_{ej} - \hat{y}_j)^2}$$

The trained Random Forest model is evaluated not only on accuracy but also on its robustness and speed. We conduct several experiments to test the model's performance under different conditions—such as using only 10% of the training data or reducing the number of available stations from five to three. Despite these limitations, the model continues to achieve high accuracy ($MAE < 5$ km), demonstrating that it is resilient and generalizable.

Once trained, the model can be deployed in a **real-time Earthquake Early Warning (EEW)** system. When a new seismic event occurs, the system receives P-wave arrival times from the first few stations. It calculates the differential times and station coordinates, passes them through the trained model, and instantly obtains an estimated

epicenter location. Because the prediction process involves only a simple pass through the Random Forest, it is **extremely fast**, taking only milliseconds.

This methodology, therefore, presents a **robust, rapid, and scalable** approach to earthquake location estimation, significantly improving upon traditional methods in both speed and flexibility. The integration of machine learning—specifically the Random Forest model—into EEW systems holds great promise for enhancing disaster preparedness and minimizing damage.

3.CONCLUSION

This project demonstrates the application of machine learning, specifically the Random Forest algorithm, for rapid and accurate estimation of earthquake source locations in Earthquake Early Warning (EEW) systems. By utilizing differential P-wave arrival times from just a few early seismic stations, the model can predict the epicenter with remarkable precision, even with limited data and station coverage. The results show a Mean Absolute Error (MAE) of 2.88 km, which is significantly lower than many traditional seismological methods. Furthermore, the model's robustness in scenarios involving only 10% of the dataset or as few as three recording stations highlights its generalizability and efficiency. The key advantages of this approach are speed, reliability, and the ability to work effectively with sparse or partial data—an essential requirement in early warning systems where every second counts. The Random Forest model, being an ensemble technique, reduces overfitting while maintaining high predictive accuracy. Its scalability allows for integration into real-time EEW systems worldwide, especially in earthquake-prone regions such as Japan, Nepal, Indonesia, and parts of the western United States.

Future work may involve the incorporation of additional features such as magnitude estimation, fault line orientation, and integration with other data modalities like

GPS and InSAR for even more comprehensive forecasting. Deep learning models and hybrid approaches may also be explored to push the boundaries of speed and precision further. Overall, this study provides a compelling case for the adoption of machine learning in enhancing the capabilities of EEW systems for disaster preparedness and risk mitigation.

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