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# Machine Learning for Fast and Reliable Source-Location Estimation in Earthquake Early Warning

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## ABSTRACT

We develop a random forest (RF) model for rapid earthquake location with an aim to assist earthquake early warning (EEW) systems in fast decision making. This system exploits P-wave arrival times at the first five stations recording an earthquake and computes their respective arrival time differences relative to a reference station (i.e., the first recording station). These differential P-wave arrival times and station locations are classified in the RF model to estimate the epicentral location. We train and test the proposed algorithm with an earthquake catalog from Japan. The RF model predicts the earthquake locations with a high accuracy, achieving a Mean Absolute Error (MAE) of 2.88 km. As importantly, the proposed RF model can learn from a limited amount of data (i.e., 10% of the dataset) and much fewer (i.e., three) recording stations and still achieve satisfactory results (MAE<5 km). The algorithm is accurate, generalizable, and rapidly responding, thereby offering a powerful new tool for fast and reliable source-location prediction in EEW

## 1.INTRODUCTION

EARTHQUAKE hypocenter localization is essential in the field of seismology and plays a critical role in a variety ofseismological applications such as tomography, source characterization,and hazard assessment. This underscores the importanceof developing robust earthquake monitoring systems foraccurately determining the event origin times and hypocenterlocations. In addition, the rapid and reliable characterizationof ongoing earthquakes is a crucial, yet challenging, task fordeveloping seismic hazard mitigation tools like earthquakeearly

warning (EEW) systems [1]. While classical methodshave been widely adopted to design EEW systems, challengesremain to pinpoint hypocenter locations in real-time largelydue to limited information in the early stage of earthquakes. Among various key aspects of EEW, timeliness is a crucial consideration and additional efforts are required to further improve the hypocenter location estimates with minimum data
from 1) the first few seconds after the P-wave arrival and 2)the first few seismograph stations that are triggered by the ground shaking.

The localization problem can be resolved using a sequence of detected waves (arrival times) and locations of seismograph stations that are triggered by ground shaking. Among various network architectures, the recurrent neural network (RNN) is capable of precisely extracting information from a sequence of input data, which is ideal for handling a group of seismic stations that are triggered sequentially following the propagationpaths of seismic waves. This method has been investigatedto improve the performance of real-time earthquakedetection [2] and classification of source characteristics. Othermachine learning based strategies have also been proposedfor earthquake monitoring. Comparisons between traditionalmachine learning methods, including the nearest neighbor,decision tree, and the support vector machine, have also beenmade for the earthquake detection problem [3]. However,a common issue in the aforementioned machine learningbased frameworks is that the selection of input features oftenrequires expert knowledge, which may affect the accuracy ofthese methods. Convolution neural networks-based clusteringmethods have been used to regionalize earthquake epicenters[4] or predict their precise hypocenter locations [5]. In thelatter case, three-component waveforms from multiple stationsare exploited to train the model for swarm event localization.

## 2.LITERATURE SURVEY

### Decision tree classifiers

Decision tree classifiers are used successfully in many diverse areas. Their most important feature is the capability of capturing descriptive decision making knowledge from the supplied data. Decision

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www.ijasem.org

Vol 18, Issue 2, 2024

tree can be generated from training sets. The procedure for such generation based on the set of objects (S), each belonging to one of the classes C1, C2, …,Ck is as follows:

Step 1. If all the objects in S belong to the same class, for example Ci, the decision tree for S consists of a leaf labeled with this class

Step 2. Otherwise, let T be some test with possible outcomes O1, O2,…, On. Each object in S has one outcome for T so the test partitions S into subsets S1, S2,…Sn where each object in Si has outcome Oi for T. T becomes the root of the decision tree and for each outcome Oi we build a subsidiary decision tree by invoking the same procedure recursively on the set Si.

**Gradient boosting**

**Gradient boosting** is a machine learning technique used in regression and classification tasks, among others. It gives a prediction model in the form of an ensemble of weak prediction models, which are typically decision trees.[1][2] When a decision tree is the weak learner, the resulting algorithm is called gradient-boosted trees; it usually outperforms random forest.A gradient-boosted trees model is built in a stage-wise fashion as in other boosting methods, but it generalizes the other methods by allowing optimization of an arbitrary differentiable loss function.

## 3. EXISTING SYSTEM

Earthquake early warning (EEW) systems are required to report earthquake locations and magnitudes as quickly as possible before the damaging S wave arrival to mitigate seismic hazards. Deep learning techniques provide potential for extracting earthquake source information from full seismic waveforms instead of seismic phase picks.

We developed a novel deep learning EEW system that utilizes fully convolutional networks to simultaneously detect earthquakes and estimate their source parameters from continuous seismic waveform streams. The system determines earthquake location and magnitude as soon as very few stations receive earthquake signals and evolutionarily improves the solutions by receiving continuous data. We apply the system to the 2016 M 6.0 Central Apennines, Italy Earthquake and its first-

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www.ijasem.org
Vol 18, Issue 2, 2024

week aftershocks. Earthquake locations and magnitudes can be reliably determined as early as 4 s after the earliest P phase, with mean error ranges of 8.5–4.7 km and 0.33–0.27, respectively.

**Disadvantages**

- An existing system method is not investigated to improve the performance of real-time earthquake detection and classification of source characteristics.
- Convolution neural networks-based clustering methods have not been used to regionalize earthquake epicenters or predict their precise hypocenter locations.

## Proposed System

The system proposes a RF-based method to locate earthquakes using the differential P-wave arrival times and station locations (Figure 1). The proposed algorithm only relies on Pwave arrival times detected at the first few stations. Its prompt response to earthquake first arrivals is critical for rapidly disseminating EEW alerts. Our strategy implicitly considers the influence of the velocity structures by incorporating the source-station locations into the RF model.

The proposed system evaluates the proposed algorithm using an extensive seismic catalog from Japan. Our test results show that the RF model is capable of determining the locations of earthquakes accurately with minimal information, which sheds new light on developing efficient machine learning.

**Advantages**

- The number of stations is a critical factor that determines the data availability and prediction accuracy. The proposed RF model takes the arrival times of P waves recorded at multiple stations as the input, hence a more stringent requirement of simultaneous recording at an increased number of stations lowers the availability of qualified events.
- The localization problem can be resolved using a sequence of detected waves (arrival times) and locations of seismograph stations that are triggered by ground shaking. Among various network architectures, the recurrent neural network (RNN) is capable of precisely extracting information from a sequence of input data, which is ideal for handling a group of seismic stations that are triggered sequentially following the propagation paths of seismic waves.

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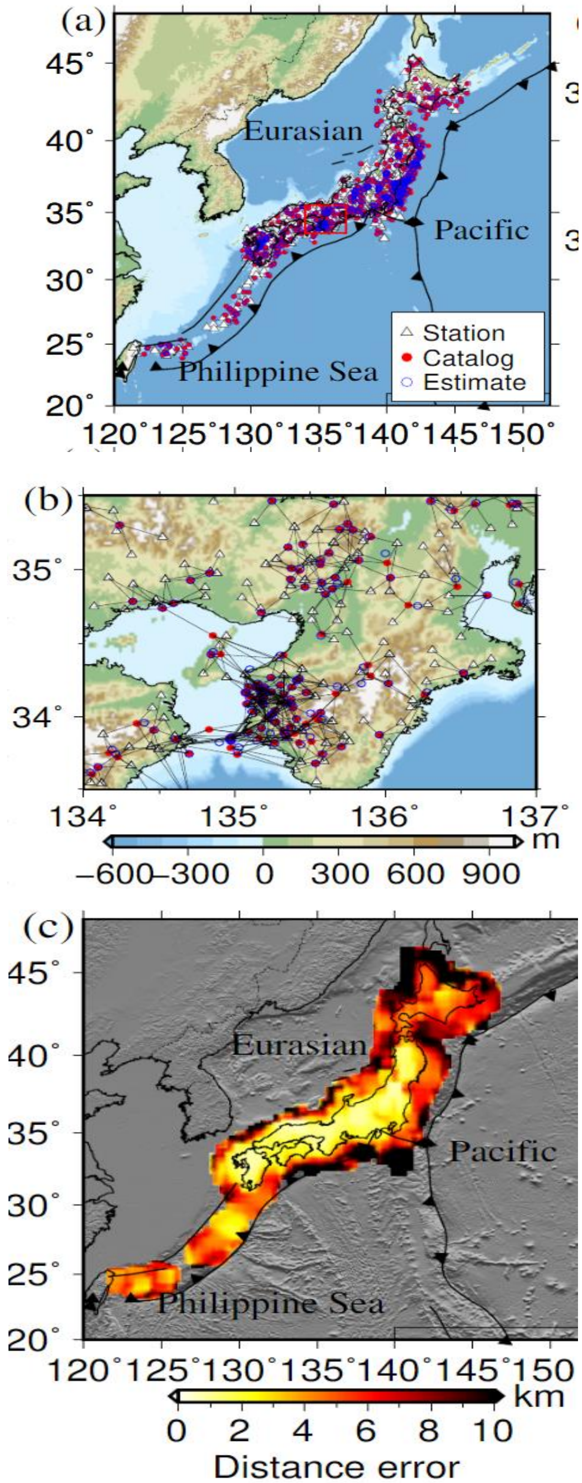
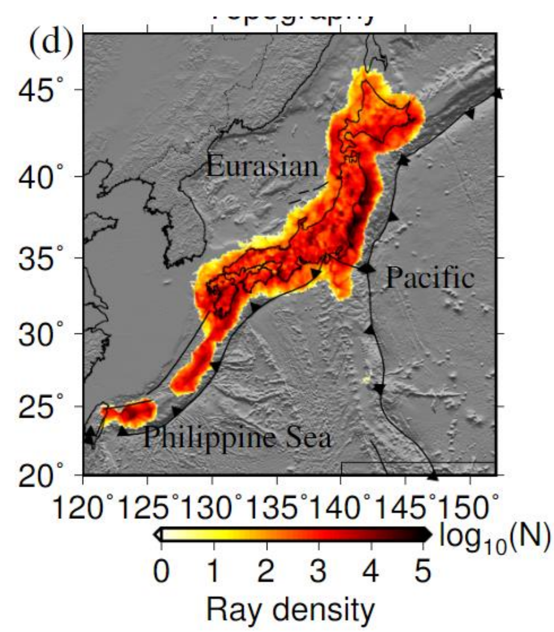
## 4. OUTPUTSCREENS




## 5. CONCLUSION

We use the P-wave arrival time differences and the location of the seismic stations to locate the earthquake in a real-time way. Random forest (RF) has been proposed to perform this regression problem, where the difference latitude and longitude between the earthquake and the seismic stations are considered as the RF output. The Japanese seismic area is used as a case of study, which demonstrates very successful performance and indicates its immediate applicability. We extract all the events having at least five P-wave arrival times from nearby seismic stations. Then, we split the extracted events into training and testing

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www.ijasem.org

Vol 18, Issue 2, 2024

datasets to construct a machine learning model. In addition, the proposed method has the ability to use only three seismic stations and 10% of the available dataset for training, still with encouraging performance, indicating the flexibility of the proposed algorithm in real-time earthquake monitoring in more challenging areas. Despite the sparse distribution of many networks around the world, which makes the random forest method difficult to train an effective model, one can use numerous synthetic datasets to compensate for the shortage of ray paths in a target area due to insufficient catalog and station distribution.

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