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.

Keywords: MAE, RF, EEW, earthquake, P wave.

I INTRODUCTION

Earthquake hypocenter localization is essential in the field of seismology andplays a critical role in a variety of seismological applications such as tomography, source characterization, and hazard assessment. This underscores the importance of developing robust earthquake monitoring systems for accurately determining the event origin times and hypo center locations. In addition, the rapid and reliable characterization of on-going earthquakes is a crucial, yet challenging, task for developing seismic hazard mitigation tools like earthquake early warning (EEW) systems. While classical methods have been widely adapted to design EEW systems, challenges remain to pinpoint hypo center locations in real-time largely due 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 thefirst few seconds after the P-wave arrival and 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 triggeredby 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. This method has been investigated to improve the performance of real time earthquake detection and classification of source characteristics. Other machine learning based strategies have also been proposed for earthquake monitoring. Comparisons between traditional machine learning methods, including the nearest neighbor, decision tree, and the support vector machine, have also been made for the earthquake detection problem.

II 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-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.

III 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.

IV.WORKING METHODOLOGY

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Service Provider

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as

Login, Train & Test Data Sets, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View Prediction Of Earthquake Early Type Warning, View Earthquake Early Warning Type Ratio, Download Predicted Data Sets, View Earthquake Early Warning Type Ratio Results, View All Remote Users.

View and Authorize Users

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, REDICT EARTHQUAKEEARLY WARNING TYPE, VIEW YOUR PROFILE.

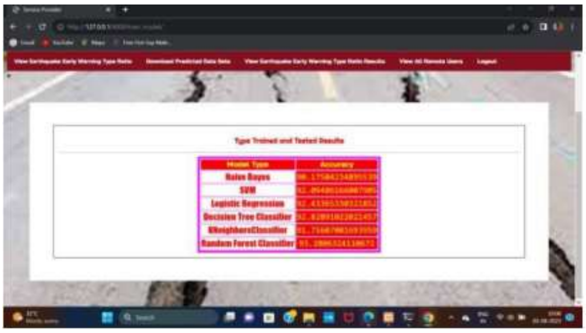

Fig.1. INPUT module.

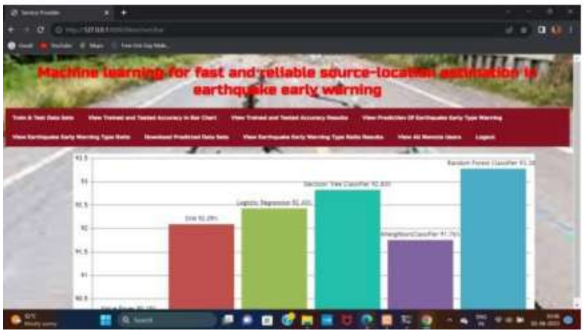

Fig.2. Output results.

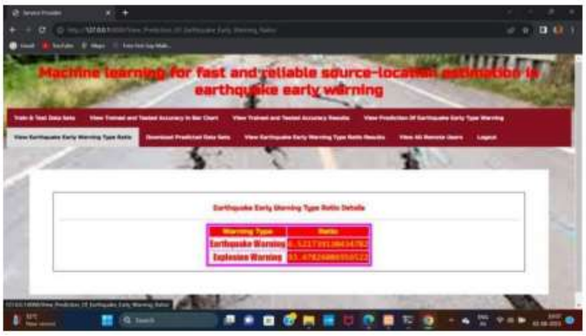

Fig.3. Accuracy level indication.

V.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 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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