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MACHINE LEARNING FOR FAST AND RELIABLE SOURC-E LOCATION ESTIMATION EARTH QUAKE 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 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 hypocenter locations. In addition, the rapid and reliable characterization of ongoing earthquakes is a crucial, yet challenging, task for developing seismic hazard mitigation tools like earthquake early warning (EEW) systems [1]. While classical methods have been widely adopted to design EEW systems, challenges remain to pinpoint hypocenter 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 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 propagation paths of seismic waves. This method has been investigated to improve the performance of real-time earthquake detection [2] 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 [3]. However, a common issue in the aforementioned machine learning based frameworks is that the selection of input features often requires expert knowledge, which may affect the accuracy of these methods. Convolution neural networks-based clustering methods have been used to regionalize earthquake epicenters [4] or predict their precise hypocenter locations [5]. In the latter case, three-component waveforms from multiple stations are exploited to train the model for swarm event localization.

In this study, we propose 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 P wave 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. We evaluate 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 [6].

2.LITERATURE SURVEY

A fast and reliable method for end-to-end estimation of earthquake magnitude from raw waveforms recorded at single stations. We design a regressor (MagNet) composed of convolutional and recurrent neural networks that is not sensitive to the data normalization, hence waveform amplitude information can be utilized during the training. The network can learn distance-dependent and site-dependent functions directly from the training data. Our model can predict local magnitudes with an average error close to zero and standard deviation of ~0.2 based on single-station waveforms without instrument response correction. We test the network for both local and duration magnitude scales and show a station-based learning can be an effective approach for improving the performance. The proposed approach has a variety of potential applications from routine earthquake monitoring to early warning systems.

The accurate and automated determination of small earthquake ($ML < 3.0$) locations is still a challenging endeavor due to low signal-to-noise ratio in data. However, such information is critical for monitoring seismic activity and assessing potential hazards. In particular, earthquakes caused by industrial injection have become a public concern, and regulators need a solid capability for estimating small earthquakes that may trigger the action requirements for operators to follow in real time. In this study, we develop a fully convolutional network and locate earthquakes induced during oil and gas operations in Oklahoma with data from 30 network stations. The network is trained by 1,013 cataloged events ($ML \geq 3.0$) as base data along with augmented data accounting for smaller events ($3.0 > ML \geq 0.5$), and the output is a 3D volume of the event location probability in the Earth. The prediction results suggest that the mean epicenter errors of the testing events ($ML \geq 1.5$) vary from 3.7 to 6.4 km, meeting the need of the traffic light system in Oklahoma, but smaller events ($ML = 1.0$, 0.5) show errors larger than 11 km. Synthetic tests suggest that the accuracy of ground truth from catalog affects the prediction results. Correct ground truth leads to a mean epicenter error of 2.0 km in predictions, but adding a mean location error of 6.3 km to ground truth causes a mean epicenter error of 4.9 km. The automated system is able to distinguish certain interfered events or events out of the monitoring zone based on the output probability estimate. It requires approximately one hundredth of a second to locate an event without the need for any velocity model or human interference.

Earthquake early warning system uses high-speed computer network to transmit earthquake information to population center ahead of the arrival of destructive earthquake waves. This short (10 s of seconds) lead time will allow emergency responses such as turning off gas pipeline valves to be activated to mitigate potential disaster and casualties. However, the excessive false alarm rate of such a system imposes heavy cost in terms of loss of services, undue panics, and diminishing credibility of such a warning system. At the current, the decision algorithm to issue an early warning of the onset of an earthquake is often based on empirically chosen features and heuristically set thresholds and suffers from excessive false alarm rate. In this paper, we experimented with three advanced machine learning algorithms, namely, K- nearest neighbor (KNN), classification tree, and support vector machine (SVM) and compared their performance against a traditional criterion-based method. Using the seismic data collected by an experimental strong motion detection network in Taiwan for these experiments, we observed that the machine learning algorithms exhibit higher detection accuracy with much reduced false alarm rate [7].

Earthquake signal detection and seismic phase picking are challenging tasks in the processing of noisy data and the monitoring of microearthquakes. Here we present a global deep-learning model for simultaneous earthquake detection and phase picking. Performing these two related tasks in tandem improves model performance in each individual task by combining information in phases and in the full waveform of earthquake signals by using a hierarchical attention mechanism. We show that our model outperforms previous deep-learning and traditional phase-picking and detection algorithms. Applying our model to 5 weeks of continuous data recorded during 2000 Tottori earthquakes in Japan, we were able to detect and locate two times more earthquakes using only a portion (less than 1/3) of seismic stations. Our model picks P and S phases with precision close to manual picks by human analysts; however, its high efficiency and higher sensitivity can result in detecting and characterizing more and smaller events.

As natural disasters are induced by geodynamic activities or abnormal changes in the environment, geological hazards tend to wreak havoc on the environment and human society. Recently, the dramatic increase in the volume of various types of Earth observation 'big data' from multiple sources, and the rapid development of deep learning as a state-of-the-art data analysis tool, have enabled novel advances in geological hazard analysis, with the ultimate aim to mitigate the devastation associated with these hazards. Motivated by numerous applications, this paper presents an overview of the advances in the utilization of deep learning for geological hazard analysis. First, six commonly available Earth observation data sources are described, e.g., unmanned aerial vehicles, satellite platforms, and in-situ monitoring systems. Second, the deep learning background and six typical deep learning models are introduced, such as convolutional neural networks and recurrent neural networks. Third, focusing on six typical geological hazards, i.e., landslides, debris flows, rockfalls, avalanches, earthquakes, and volcanoes, the deep learning applications for geological hazard analysis are reviewed, and common application paradigms are summarized. Finally, the challenges and opportunities for the application of deep learning models for geological hazard analysis are highlighted, with the aim to inspire further related research.

3. PROBLEM STATEMENT

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 [8].

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3.1 Disadvantages

In 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.

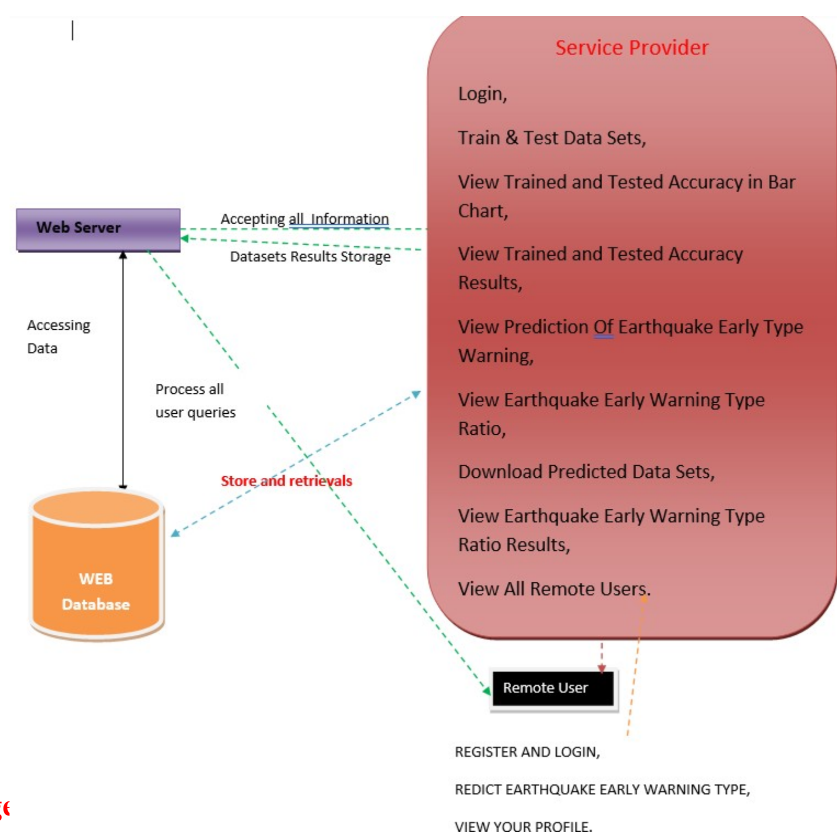
4.PROPOSED SYSTEM

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.

4.1 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 [8].

5. SYSTEM ARCHITECTURE



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6. IMPLEMENTATION

6.1 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.

6.2 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.

6.3 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 EARTHQUAKE EARLY WARNING TYPE, VIEW YOUR PROFILE.

Data Collection and Preprocessing:

- Module for collecting earthquake-related data from various sources such as seismographs, GPS sensors, and historical earthquake databases.
- Preprocessing module to clean, filter, and format the collected data for further analysis.

Feature Engineering:

- Module for extracting relevant features from raw data that can be used for source location estimation.

- Techniques might include time-series analysis, frequency domain analysis, and spatial feature extraction.

Machine Learning Models:

- Module containing implementations of machine learning algorithms for source location estimation.
- This might include supervised learning algorithms such as Support Vector Machines (SVM), Random Forest, Gradient Boosting, or deep learning models like Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs).
- Unsupervised learning techniques such as clustering algorithms could also be explored for anomaly detection or data exploration.

Real-Time Data Processing:

- Module for processing incoming data streams in real-time for early earthquake detection and estimation.
- Efficient algorithms and data structures to handle high-volume data streams and make quick predictions.

Integration with Seismic Sensors and Networks:

- Module to interface with seismic sensors and networks to receive real-time data updates.
- Implementation of communication protocols and APIs for seamless integration with sensor networks.

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7. OUTPUT RESULTS

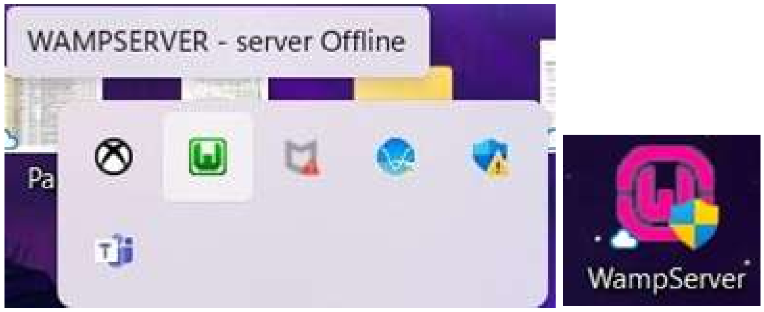

Fig:-7.1RunWampServerinthebackground

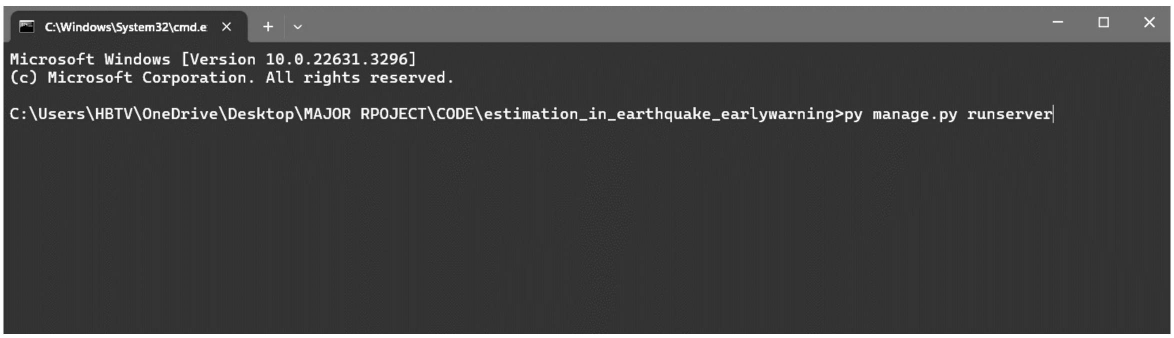

Fig:-7.2Runtheprojectfileinthecommandprompt

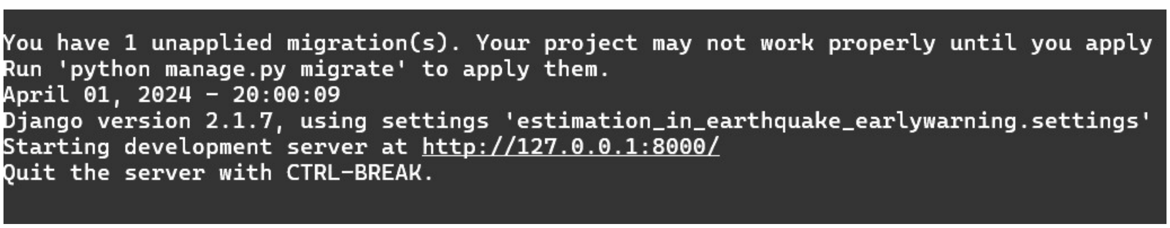

Fig:-7.3Pastetheserverinthebrowser

Fig:-7.4Interfaceoftheproject

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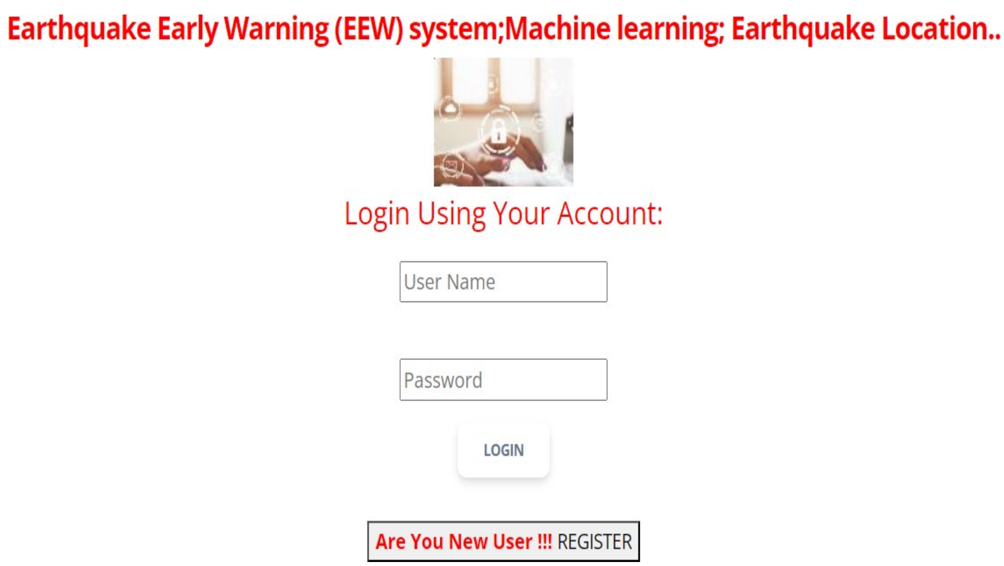

Fig:-7.5UserLoginInterface

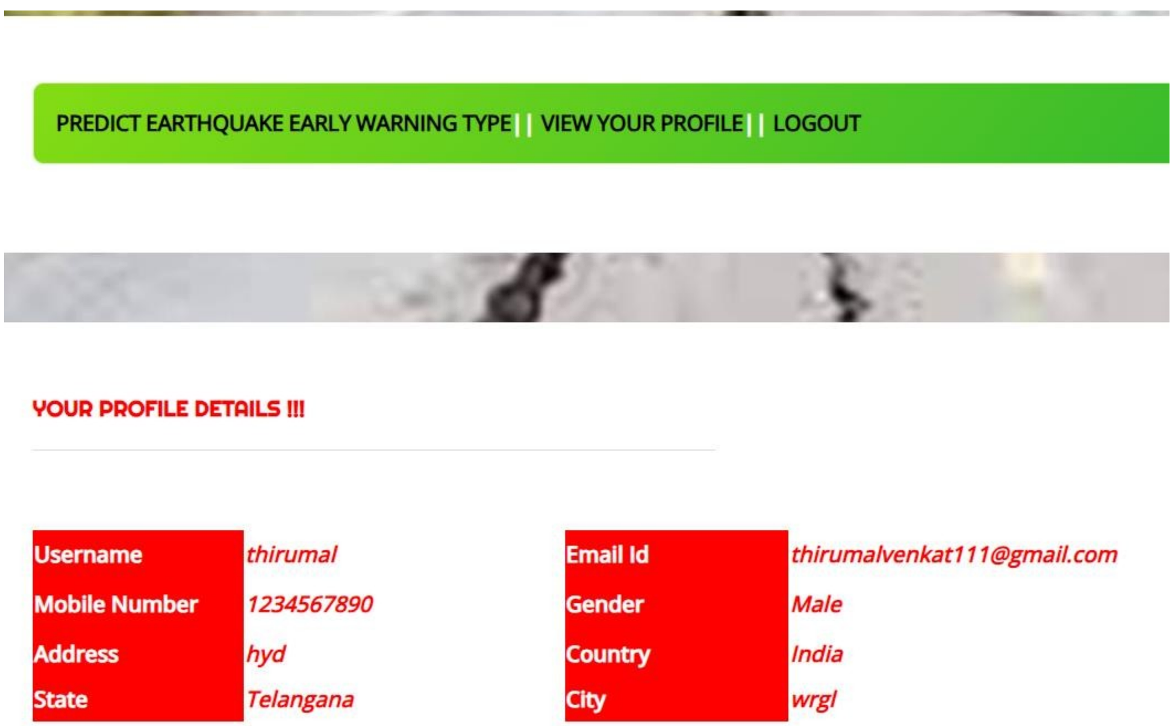

Fig7.6AfterLogin

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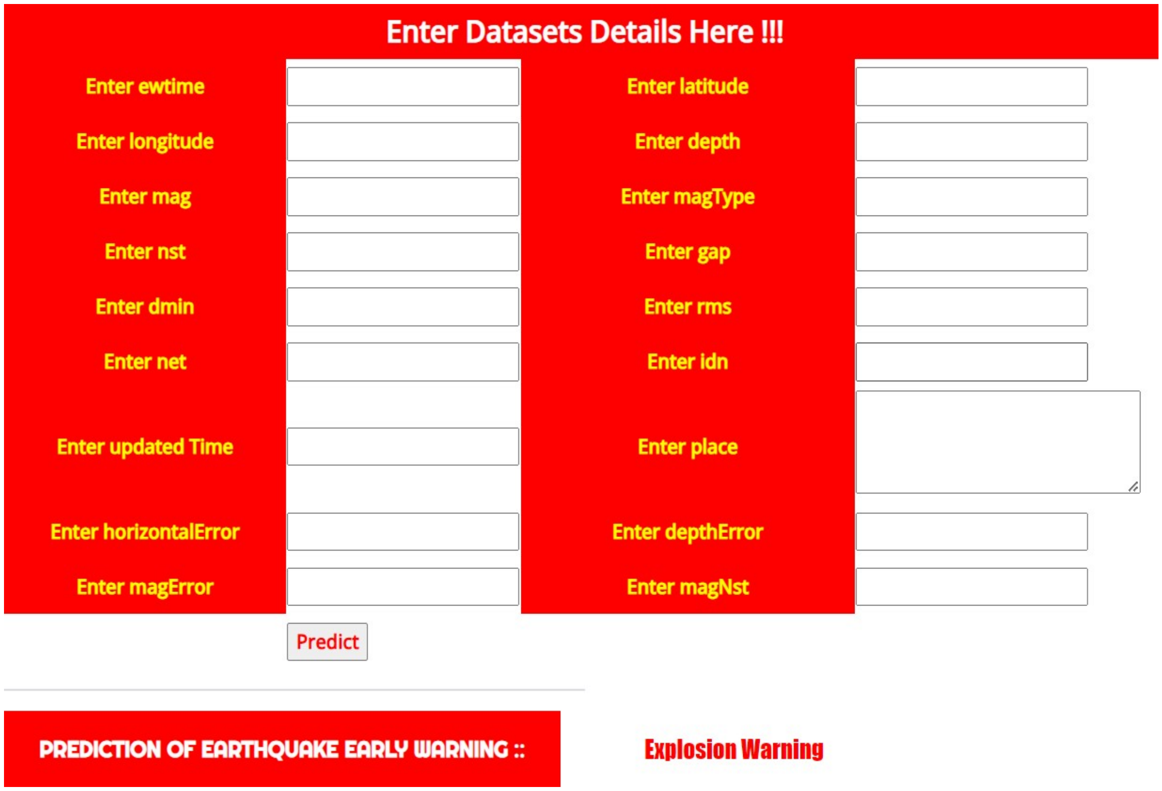

Fig7.7Outputforthegivenvalues

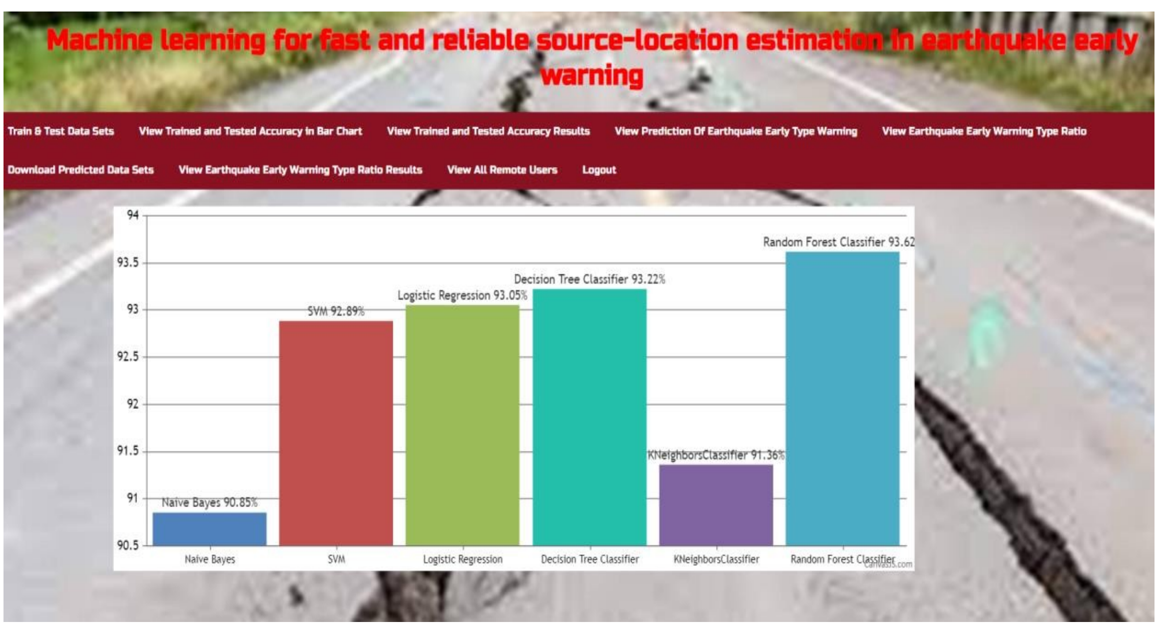

Fig 7.8Accuracyrate forthe traineddata sets

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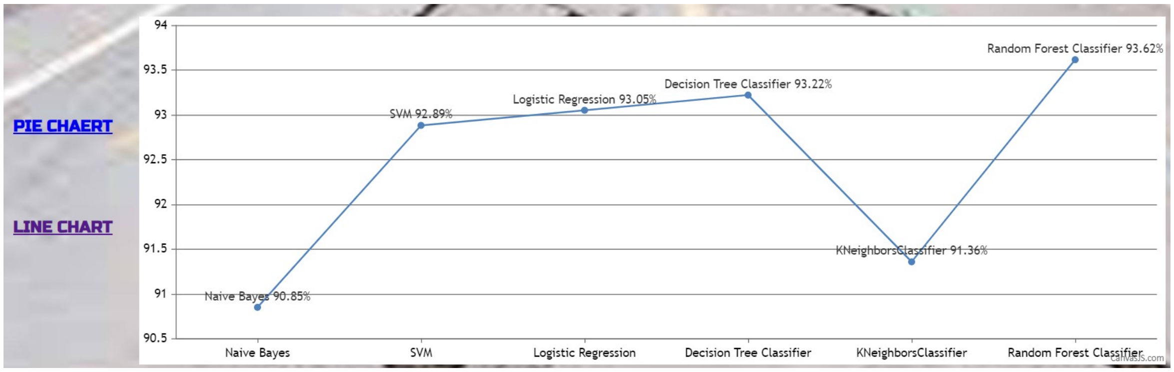

Fig7.9LineGraph

8.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.

9. FUTURE SCOPE

The Continued research and development efforts will focus on further optimizing machine learning algorithms, advancing signal processing techniques, and enhancing collaboration among stakeholders to continuously improve earthquake early warning systems. Additionally, ongoing efforts will be directed towards adapting the system to evolving seismic conditions and integrating emerging technologies for more comprehensive and effective earthquake risk mitigation.

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