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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)

I.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 . 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 the first few seconds after the P-wave arrival and he 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 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. 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 or predict their precise hypocenter locations

II.LITERATURE SURVEY

“Using Machine Learning to Estimate Source Location Early Earthquake Warning” Authors: Radha R.*1, Prakash Babu Yandrapati2, M. Abirami3, G. Victo Sudha George4, A.Joshi5 Early warning systems for earthquakes can mitigate their destructive potential by spreading information about the quake's magnitude and location long before destructive waves reach populated areas. Source-location estimations in these systems need to be timely and accurate for them to be useful. This study presents a novel approach for enhancing the precision and speed of seismic early warning using machine learning techniques. Timely warnings may be delayed due to the precision but slowness of traditional seismic techniques for calculating earthquake sites. The purpose of the random forest (RF) model for fast earthquake localization is to aid in the quick decision making required by earthquake early warning (EEW) systems. This approach takes use of the P-wave arrival times recorded by the first five stations to record an earthquake and calculates the variations in these timings with regard to the first station. In order to determine the epicenter, the RF model categorizes these differences in Pwave arrival timings and station locations. The model is used to train and validate the proposed method using a Japanese earthquake dataset. The RF model is quite accurate in predicting earthquake epicenters, with a Mean Absolute Error (MAE) of just 2.88 kilometers. Additionally, the suggested RF model may learn from as little as 10% of the information and as little as three recording stations while still producing usable results (MAE5 km) in most cases. This novel algorithm provides a robust and flexible method for predicting the location of EEW sources in real-time. “An IEEE21451-001 Compliant Smart Sensor for Early Earthquake Detection” Authors: Marco Carrattu, Member, IEEE, Salvatore Dello Iacono, Member, IEEE, Vincenzo Paciello, Senior Member, IEEE, Antonio Espírito-Santo, Member, IEEE, Gustavo Monte, Member, IEEE This paper introduces a novel smart sensor that employs an advanced algorithm for earthquake early warning (EEW). The sensor utilizes a smart sampling technique to extract 3 significant signal information, simplifying the process of inferring

knowledge. The main objective is to assess the potential destructiveness of an incoming earthquake by analyzing the initial moments of the

P-wave, and to generate an alert for prompt action, if necessary. The study includes the development and presentation of the proposed method, as well as performance evaluations using real seismic data obtained from freely accessible databases. These evaluations confirm the effectiveness of the proposed method in accurately estimating earthquake magnitudes. Furthermore, the paper includes a comparison with a widely used EEW algorithm. The real-time functionality and interoperability of devices are crucial considerations in earthquake detection applications. The suitability and compatibility of the proposed method with the IEEE1451 family of standards are demonstrated and emphasized in the paper.

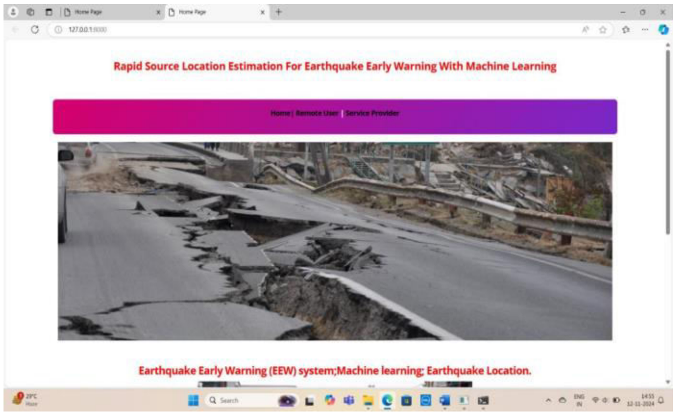


Figure No-4.1 Home page

III.SYSTEM ARCHITECTURE:

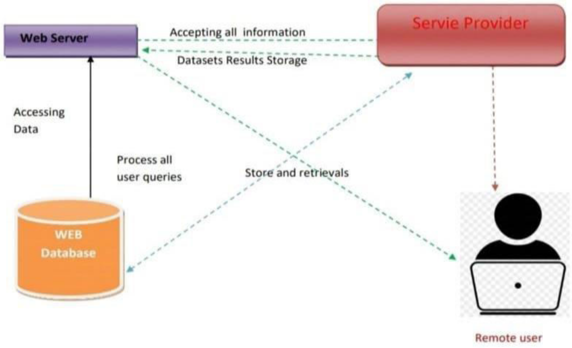


Fig 4.1 Architecture Diagram

IV.OUTPUT SCREENS

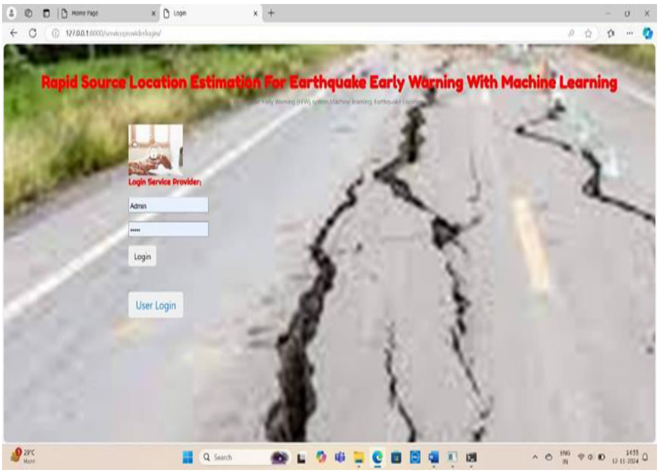
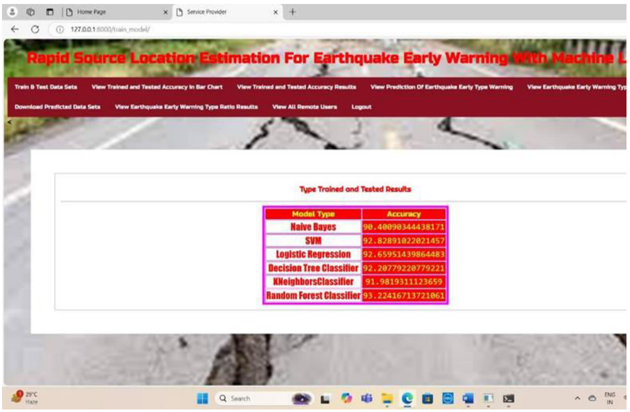


Figure No-4.2 Login page



Type Trained and Tested Results

Model Type	Accuracy
Naive Bayes	90.40090344438171
SVM	92.82891022021457
Logistic Regression	92.65951439864483
Decision Tree Classifier	92.20779220779221
KNeighborsClassifier	91.9819311123659
Random Forest Classifier	93.22416713721061

Figure No-4.3 various algorithms with accuracy

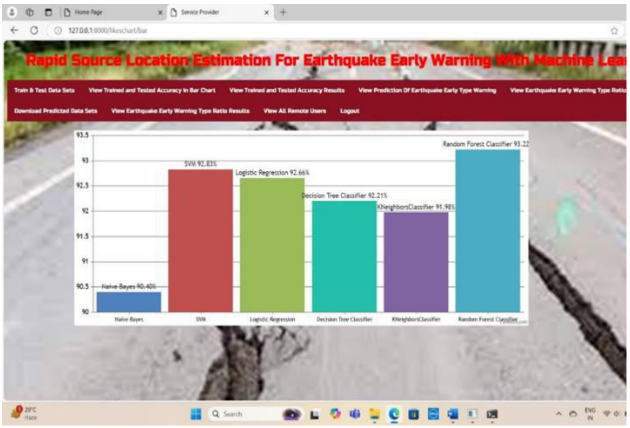
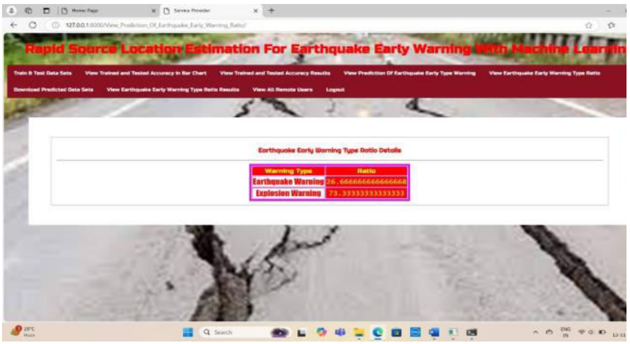


Figure No-4. 4 View accuracy in bar chart



Earthquake Early Warning Type Ratio Details

Warning Type	Ratio
Earthquake Warning	26.666666666666668
Explosion Warning	73.33333333333333

Figure No-4. 5 EEW Ratio

PREDICTION OF EARTHQUAKE EARLY WARNING :: Earthquake Warning

Figure No -4.6 Prediction page

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 usedas 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 trainan effective model, one can use numerous synthetic datasets to compensate for the shortageof ray paths in a target area due to insufficient catalog and station distribution. The future of earthquake early warning is promising, driven by advances in technology, data analytics, and global cooperation. With improvements in speed, accuracy, and publiccommunication, EEW systems will become even more effective at saving lives, protecting infrastructure, and mitigating the social and economic impacts of earthquakes. However, ensuring widespread adoption and accessibility, especially in high-risk regions, will be essential to making these advancements a reality.

VI. FUTURE ENHANCEMENT

The future enhancement of earthquake early warning (EEW) systems is focused on improving detection speed, increasing accuracy, broadening coverage, and providing more useful information to individuals and organizations in the event of an earthquake. Here are several key areas where enhancements are likely to occur in the coming years:

1.Faster Detection and Alerting:

Advanced Seismic Networks: The deployment of more dense and advanced seismic sensor networks will help detect earthquakes more quickly, especially small to moderate events that may otherwise be missed or detected too late for effective warning.

Machine Learning and AI: Integrating machine learning algorithms can help in processing seismic data faster, identifying patterns of seismic waves that indicate a strong earthquake, and issuing alerts sooner. AI could also be used to improve the accuracy of determining earthquake magnitude and location in real-time.

Real-Time Processing: Improvements in real-time data processing capabilities, such as edge computing (where data is processed closer to the source), could further reduce the time from earthquake detection to alert issuance.

2.Improved Accuracy of Magnitude and Location Estimations:

Multi-Point Detection: The use of more seismic stations and other geophysical sensors (e.g., accelerometers, GPS, and strain meters) will allow for better triangulation of earthquake epicenter and more precise estimates of magnitude.

Early Warning via Strong Motion Prediction: Advanced algorithms that predict the extent of shaking based on real-time sensor data will improve the precision of the alerts. For example, rather than just issuing an alert based on magnitude, future systems might predict ground shaking intensities more specifically for different locations.

3.Integration of Multiple Data Sources:

Satellite Data: Combining data from satellites (e.g., radar-based satellite systems like InSAR) could provide real-time insights into ground deformations caused by seismic activity, enhancing the ability to detect earthquakes and assess their potential impacts. Broadband Communication and IoT: The use of the Internet of Things (IoT) for collecting data from a variety of sensors (e.g., smart buildings, transportation networks, critical infrastructure) can provide additional information to improve the precision of early warnings.

VII. REFERENCES

[1]Q. Kong, R. M. Allen, L. Schreier, and Y.-W. Kwon, " My shake: A smartphone seismic network for earthquake early warning and beyond," Science advances, vol. 2,no. 2, p. e1501055, 2016.

[2]T.-L. Chin, K.-Y. Chen, D.-Y. Chen, and D.-E. Lin, "Intelligent real-time earthquake detection by recurrent neural networks," IEEE Transactions on Geoscience and Remote Sensing, vol. 58, no. 8, pp. 5440–5449, 2020.

[3]T.-L. Chin, C.-Y. Huang, S.-H. Shen, Y.-C. Tsai, Y. H. Hu, and Y.-M. Wu, "Learn to detect: Improving the accuracy of earthquake detection," IEEE Transactions on Geoscience and Remote Sensing, vol. 57, no. 11, pp. 8867–8878, 2019.

[4]O. M. Saad, A. G. Hafez, and M. S. Soliman, "Deep learning approach for earthquake parameters classification in earthquake early warning system," IEEE Geoscience and Remote Sensing Letters, pp. 1–5, 2020.

[5]X. Zhang, J. Zhang, C. Yuan, S. Liu, Z. Chen, and W. Li, "Locating induced earthquakes with a network of seismic stations in oklahoma via a deep learning method," Scientific reports, vol. 10, no. 1, pp. 1–12, 2020.

[6]L. Breiman, "Random forests," Machine learning, vol. 45, no. 1, pp. 5–32, 2001.

[7]S. M. Mousavi, W. L. Ellsworth, W. Zhu, L. Y. Chuang, and G. C. Beroza, "Earthquake transformer an attentive deep-learning model for simultaneous earthquake detection and phase picking," Nature Communications, vol. 11, no. 1, pp. 1–12, 2020.

[8]S. M. Mousavi and G. C. Beroza, "A Machine- Learning Approach for Earthquake Magnitude Estimation," Geophysical Research Letters, vol. 47, no. 1, p. e2019GL085976, 2020.