

ENHANCING EARTHQUAKE EARLY WARNING: ACCELERATING AND IMPROVING SOURCE-LOCATION ESTIMATION WITH MACHINE LEARNING

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ABSTRACT

Vehicle accident is the paramount threat for the people's life which causes a serious wound or even dead. The automotive companies have made lots of progress in alleviating this threat, but still the probability of detrimental effect due to an accident is not reduced. This app presents a real-time solution for this problem by providing an accident detection and alert system and notification to police and ambulance drivers. This is done by using commonly available electronic devices that are mobile phones to detect the accident. An Android smartphone with an integrated accelerometer is used for crash detection. Accelerometer will evaluate the acceleration frequency with which the phone has to detect the crash. The threshold is evaluated based on parameters such as height and frequency of vibrations. If it's higher than the set threshold then the app is ready to make a call and send the SMS to police and ambulance and saved contacts along with the GPS location of last crashed point. As same like Accelerometers sound meter also used to get the noise frequency of vehicle. If any crash happened then sound meter can get the sound and if it's higher than the set threshold then the app can perform same as above.

KEYWORDS: Accelerometers Sound meter, GPS and SMS alert, Crash detection, android smartphones

1. INTRODUCTION

The localization of earthquake hypocenters is paramount in seismology, serving as a foundational element in various seismic applications such as tomography, source characterization, and hazard assessment. With the growing need for accurate and rapid earthquake monitoring systems, the importance of precise determination of event origin times and hypocenter locations cannot be overstated. This paper explores the challenges and advancements in earthquake hypocenter localization, particularly in the context of seismic hazard mitigation tools like earthquake early warning (EEW) systems.

Challenges in Earthquake Hypocenter Localization: Classical methods for earthquake monitoring often face challenges in pinpointing hypocenter locations in real-time, primarily due to limited information available in the early stages of seismic events. This limitation becomes particularly pronounced in the first few seconds after the arrival of primary (P) waves and with data from only a few seismograph stations that are triggered by the initial ground shaking. Despite advancements in seismic instrumentation and data processing techniques, achieving timely and accurate hypocenter localization remains a significant challenge.

Advancements in Early Earthquake Warning Systems: Efforts to enhance hypocenter localization in real-time have led to the development of advanced EEW systems. These systems leverage innovative algorithms and real-time data processing techniques to rapidly assess seismic events and provide timely warnings to mitigate potential hazards. By utilizing data from the first few seconds after the P-wave arrival and the initial triggered seismograph stations, modern

EEW systems aim to improve the accuracy of hypocenter location estimates while prioritizing timeliness in issuing warnings.

Key Considerations in Enhancing Hypocenter Localization: Timeliness emerges as a crucial consideration in the development of effective EEW systems. To achieve timely and accurate hypocenter localization, additional efforts are required to optimize data processing algorithms, integrate real-time seismic data from multiple sources, and improve the spatial coverage of seismograph networks. Furthermore, advancements in sensor technology and communication infrastructure play a vital role in enhancing the early detection and characterization of seismic even.

2. LITERATURE SURVEY

[1] ENHANCING EARTHQUAKE EARLY WARNING: ACCELERATING AND IMPROVING SOURCE-LOCATION ESTIMATION WITH MACHINE LEARNING

The literature survey on Earthquake Early Warning (EEW) systems reveals significant advancements in the field. The study “Myshake: A smartphone seismic network for earthquake early warning and beyond” by Qingkai Kong in 2018 emphasizes the importance of EEW systems in providing crucial seconds to minutes of warning, allowing people to move to safe zones and enabling automated slowdown and shutdown of transit and other machinery.

In 2020, Dayi Chen’s study “Intelligent real-time earthquake detection by recurrent neural networks” highlights the critical role of fast and reliable detection for the presence of earthquakes in EEW systems. The study underscores the importance of real-time earthquake detection using recurrent neural networks to avoid severe loss.

Chin-Ya Huang, in his 2020 study “Learn to detect: Improving the accuracy of earthquake detection,” discusses how short lead times (10s of seconds) can enable emergency responses such as turning off gas pipeline valves to mitigate potential disaster and casualties.

In 2022, Ali G. Hafez’s study “Deep learning approach for earthquake parameters classification in earthquake early warning system” points out that the beneficiaries of EEW systems depend on how far they are located from such strong events.

Lastly, Xiong Zhang’s 2018 study “Locating induced earthquakes with a network of seismic stations in Oklahoma via a DL method” brings attention to the public concern over earthquakes caused by industrial injection.

In conclusion, the literature suggests that advancements in machine learning and deep learning are playing a pivotal role in enhancing the effectiveness of EEW systems. These advancements are not only improving the accuracy of earthquake detection but also helping in mitigating the potential disasters and casualties caused by earthquakes.

3. METHODOLOGY

3.1 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. In Existing, 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. 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.

3.1.1 DISADVANTAGES OF EXISTING SYSTEM

- 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.

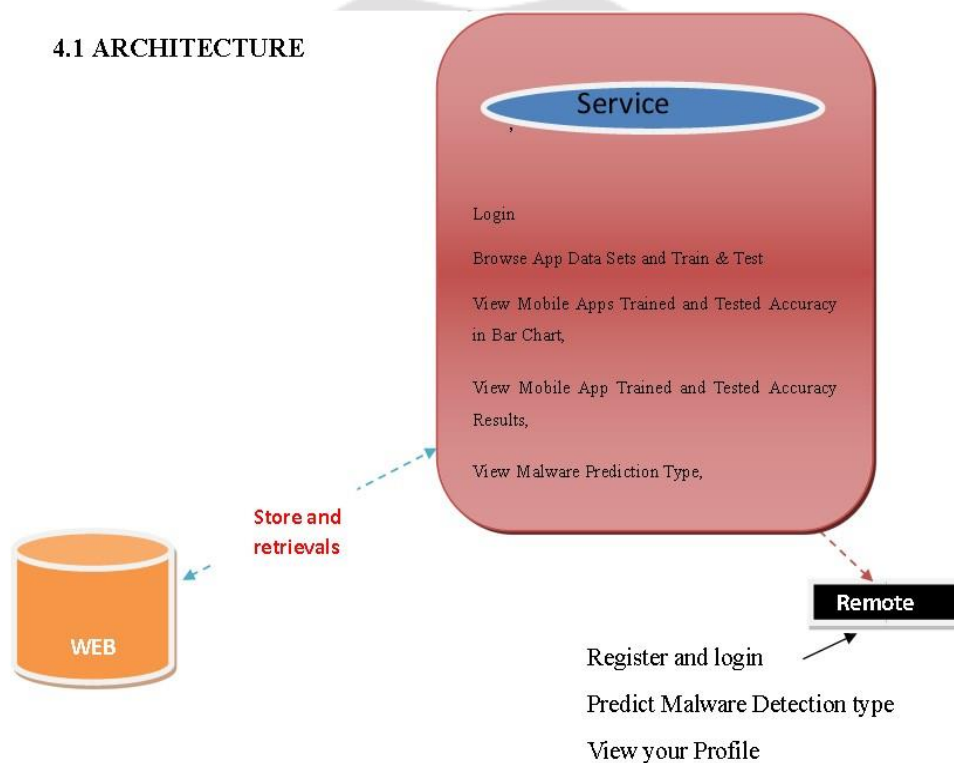
3.2 PROPOSED METHODOLOGY

The system proposes a RF-based method to locate earthquakes using the differential Pwave arrival times and station locations. 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. 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. SYSTEM DESIGN

It is a process of planning a new business system or replacing an existing system by defining its components or modules to satisfy the specific requirements. Before planning, you need to understand the old system thoroughly and determine how computers can best be used in order to operate efficiently.

4.1 ARCHITECTURE



4.2 MODULES

In this Proposed System, there are two Modules. They are:

1. Service Provider
2. Remote User

4.2.1 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. > Log Out

4.2.2 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 ➤ Predict Earthquake early Warning Type ➤ View Your Profile. ➤ Log Out

5. RESULTS AND PERFORMANCE

EXECUTION PROCEDURE

The Execution procedure is as follows:

1. In this research work with data with attributes are observable and then all of them are floating data. And there's a decision class/class variable. This data was collected from Kaggle machine learning repository.
2. In this research 70% data use for train model and 30% data use for testing purpose.
3. Random Forest is used as Classifier.
4. In the classification report we were able to find out the desired result
5. In this analysis the result depends on some part of this research. However, which algorithm gives the best true positive, false positive, true negative, and false negative are the best algorithms in this analysis.

The image shows a code editor window with a project named 'estimation_in_earthquake_earlywarning'. The 'settings.py' file is open, showing the following configuration:

```

'DATABASES' = {
    'default': {
        'ENGINE': 'django.db.backends.mysql',
        'NAME': 'earthquake_earlywarning',
        'USER': 'root',
        'PASSWORD': '1234',
        'HOST': '127.0.0.1',
        'PORT': '3306',
    }
}

AUTH_PASSWORD_VALIDATORS = [
    {'NAME': 'django.contrib.auth.password_validation.UserAttributeSimilarity'},
    {'NAME': 'django.contrib.auth.password_validation.MinimumLength'},
    {'NAME': 'django.contrib.auth.password_validation.CommonPasswordCheck'},
    {'NAME': 'django.contrib.auth.password_validation.NumericPasswordCheck'},
]

# Password validation
# https://docs.djangoproject.com/en/3.2/ref/settings/#auth-password-validators

```

The terminal window shows the command being executed:

```

E:\estimation_in_earthquake_earlywarning>python manage.py runserver

```

Fig. Running Program on console

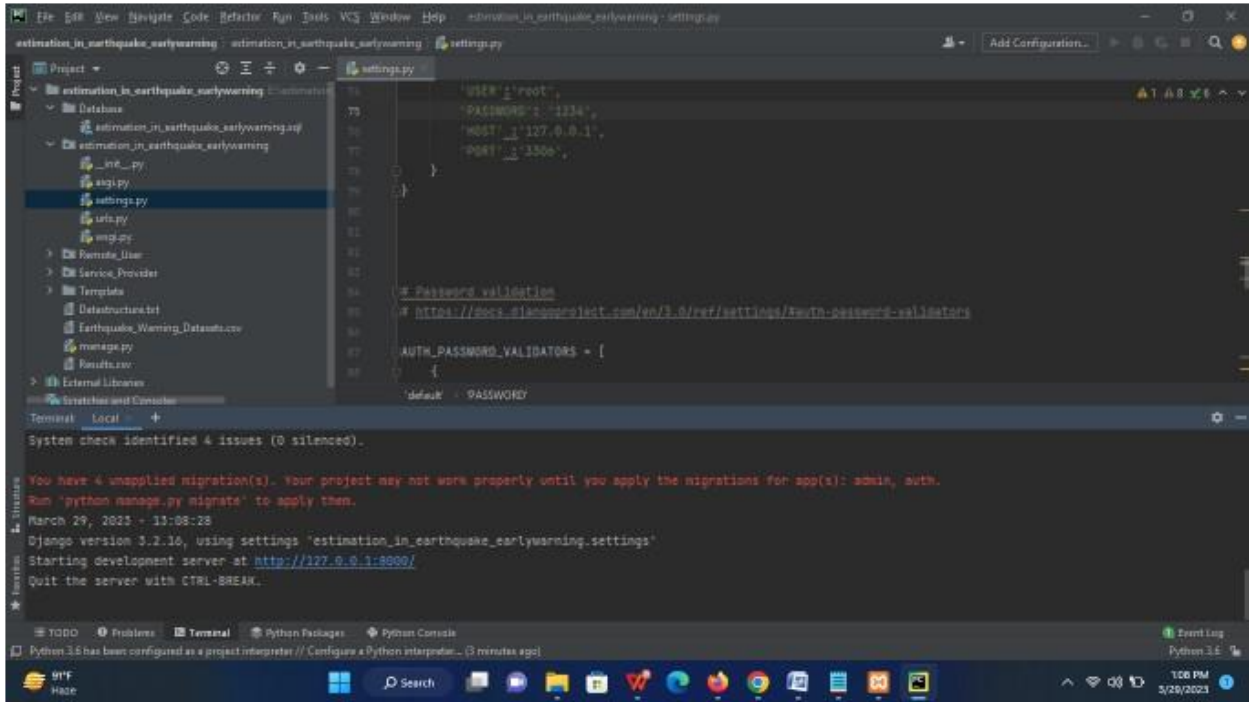


Fig. Generating Link

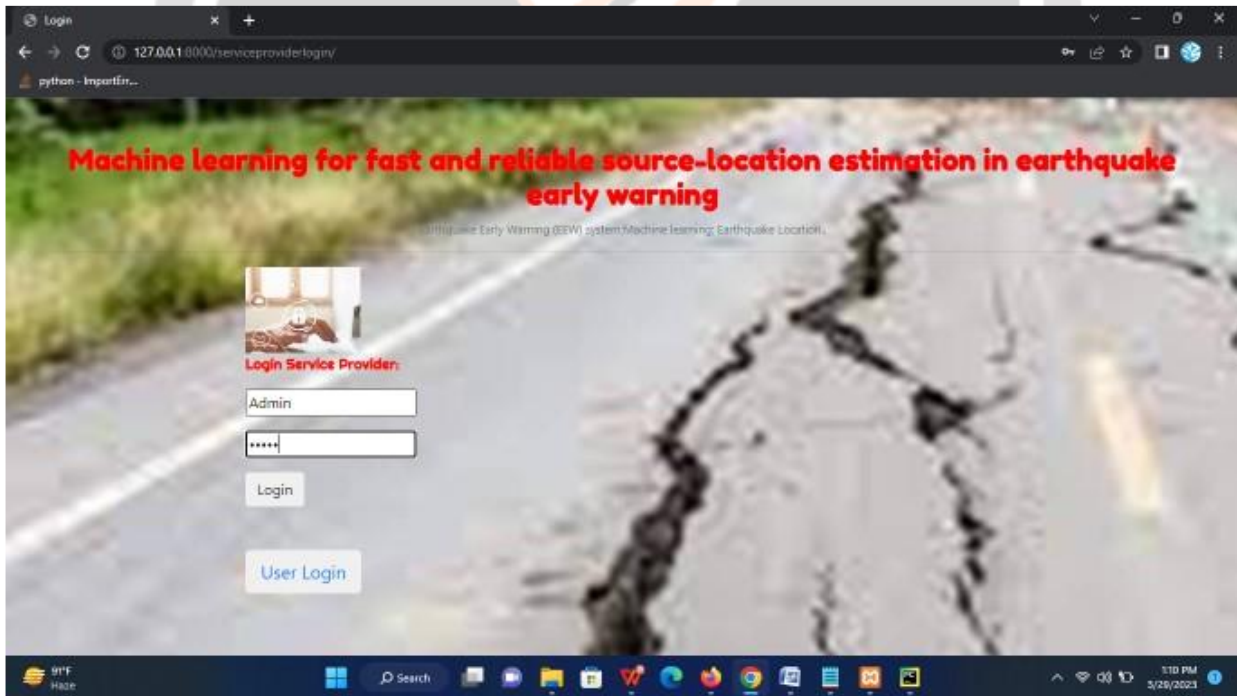


Fig. Service Provider Login

time	latitude	longitude	depth	mag	magType	nct	gap	dmin	rms	net	id	updated	place	horizontalE	depthError	magError	magInst
2022-08-25	33.401	-116.4352	10.4	0.78	ml		34	60	0.1119	0.21	ci	2022-08-25	17km NNW	0.3	0.66	0.127	
2022-08-25	33.9805	-116.8328	16.95	0.98	ml		30	47	0.05835	0.14	ci	2022-08-25	7km NNE of	0.24	0.62	0.151	
2022-08-25	36.044998	-120.609	4.36	0.78	md		8	205	0.02593	0.06	nc	2022-08-25	23km NW of	1.3	2.3	0.06	
2022-08-25	19.181833	-155.3537	28.360001	2.3	ml		43	183	0.13	hw	hw73118262	2022-08-25	13 km E of I	0.59	0.95	0.12	
2022-08-25	33.846833	-116.8737	14.75	0.94	ml		30	49	0.1159	0.19	ci	2022-08-25	9km S of Ba	0.26	0.67	0.137	
2022-08-25	35.674	-117.4415	1.06	1.1	ml		11	127	0.1614	0.22	ci	2022-08-25	11km SSW of	0.55	1.12	0.158	
2022-08-25	19.189167	-155.5107	35.779999	2.2	ml		47	90	0.11	hw	hw73118182	2022-08-25	3 km WSW of	0.48	0.87	0.24	
2022-08-25	17.914	-101.4956	35	4.3	mb		31	236	1.742	0.76	us	2022-08-25	18 km W of	4.72	1.997	0.036	
2022-08-25	-15.0823	-178.5647	375.794	4.3	mb		33	130	0.882	0.57	us	2022-08-25	97 km SSW of	13.91	7.572	0.054	
2022-08-25	38.188	-117.7767	10.2	0.9	ml		10	193.8	0.124	0.0886	nn	2022-08-25	36 km SE of Mina, Neva	0.8	0.8	0.41	
2022-08-25	41.2125	-121.8602	7.75	1.84	md		31	59	0.11	nc	nc73770855	2022-08-25	22km N of E	0.22	0.63	0.186	
2022-08-25	18.887167	-155.2355	6.36	2.5	md		28	256	0.17	hw	hw73118102	2022-08-25	41 km ESE of	0.52	0.81	0.1755103	
2022-08-25	18.980667	-65.896	20.07	2.9	md		14	265	0.2	pr	pr71367508	2022-08-25	60 km N of	1.03	18.36	0.0769419	
2022-08-25	-52.5504	-71.7165	35.032	4.2	mb		26	150	0.32	0.72	us	2022-08-25	86 km NW of	5.91	8.936	0.128	
2022-08-25	58.220833	-155.1875	12.04	-0.06	ml		5	180	0.33	av	av91667086	2022-08-25	84 km NNW	1.26	1.94	0.2294875	
2022-08-22	18.0366	-68.486	83	3.85	md		25	206	1.0652	0.49	pr	2022-08-25	39 km SSE of	2.11	1.88	0.18	
2022-08-22	38.83734	-122.7907	2	0.85	md		7	77	0.001103	0.02	nc	2022-08-25	6km WNW of	0.52	1.47		
2022-08-22	18.202167	-66.201	16.67	2.27	md		10	94	0.26	pr	pr71367483	2022-08-25	3 km ESE of	0.68	0.82	0.1317944	
2022-08-22	34.010833	-118.4203	12.95	1.31	ml		22	88	0.02426	0.18	ci	2022-08-25	2km WSW of	0.38	0.36	0.185	
2022-08-22	19.1975	-155.4845	32.91	2.42	ml		50	82	0.11	hw	hw73118047	2022-08-25	0 km SW of	0.43	0.58	0.1656933	
2022-08-22	33.468133	-116.425	14.26	0.8	ml		22	80	0.05393	0.12	ci	2022-08-25	24km SSW of	0.25	0.53	0.138	
2022-08-22	35.033333	-117.6843	-0.8	1.56	ml		19	79	0.0992	0.15	ci	2022-08-25	5km NW of	0.47	31.61	0.112	

Fig: Earth Quake Dataset

```
estimation_in_earthquake_earlywarning - settings.py
Project
  estimation_in_earthquake_earlywarning
    Database
      estimation_in_earthquake_earlywarning.sql
    estimation_in_earthquake_earlywarning
      _fit_.py
      _score_.py
Terminal Local
[[ 408 64]
 [ 86 1213]]
RNNNeighborsClassifier
ACCURACY
90.73969508752117
CLASSIFICATION REPORT
precision recall f1-score support
0 0.82 0.84 0.83 472
1 0.94 0.93 0.94 1299
accuracy 0.91 1771
macro avg 0.88 0.89 0.88 1771
weighted avg 0.91 0.91 0.91 1771
CONFUSION MATRIX
[[ 397 75]
 [ 89 1210]]
Random Forest Classifier
```

Fig: Training with ML Algorithms

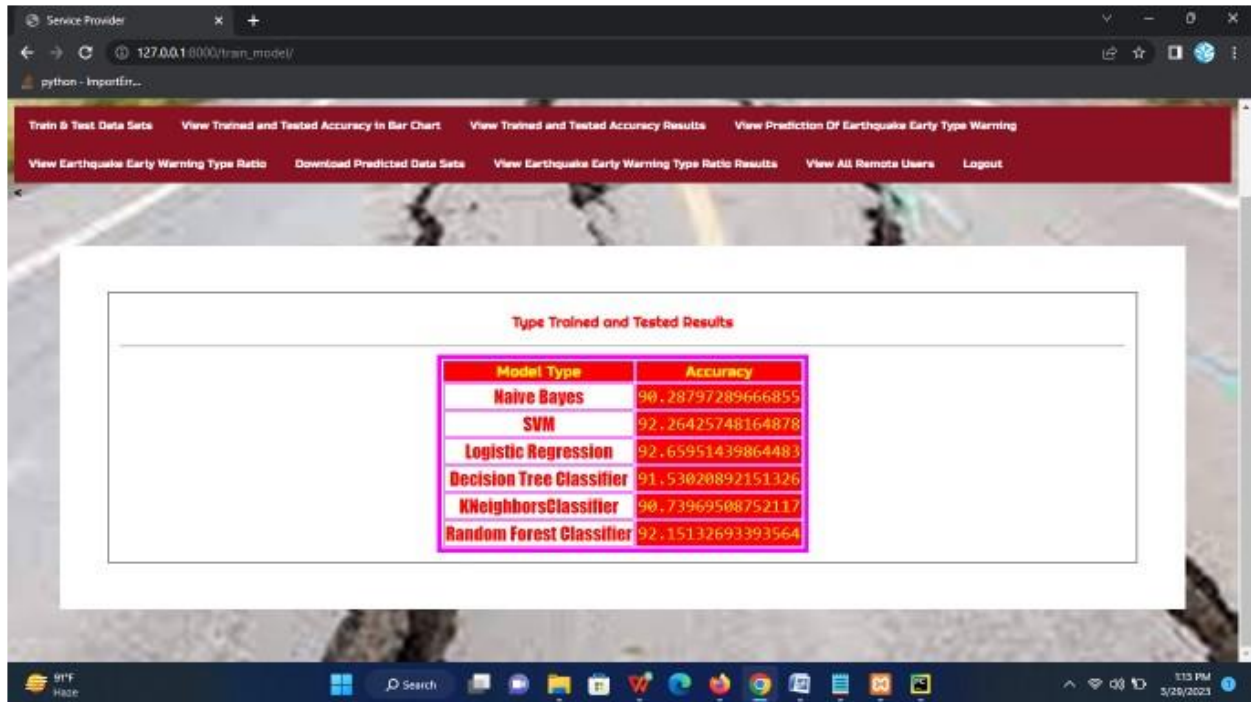


Fig: Trained and Tested results

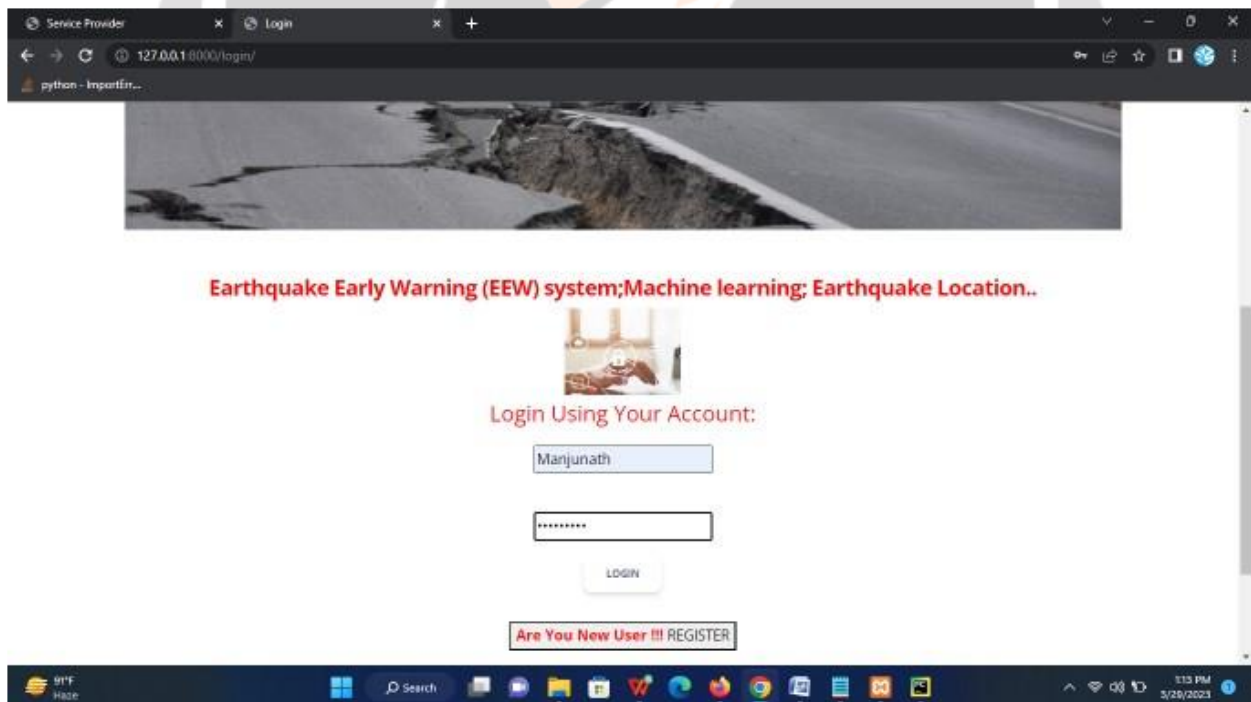


Fig: User Login

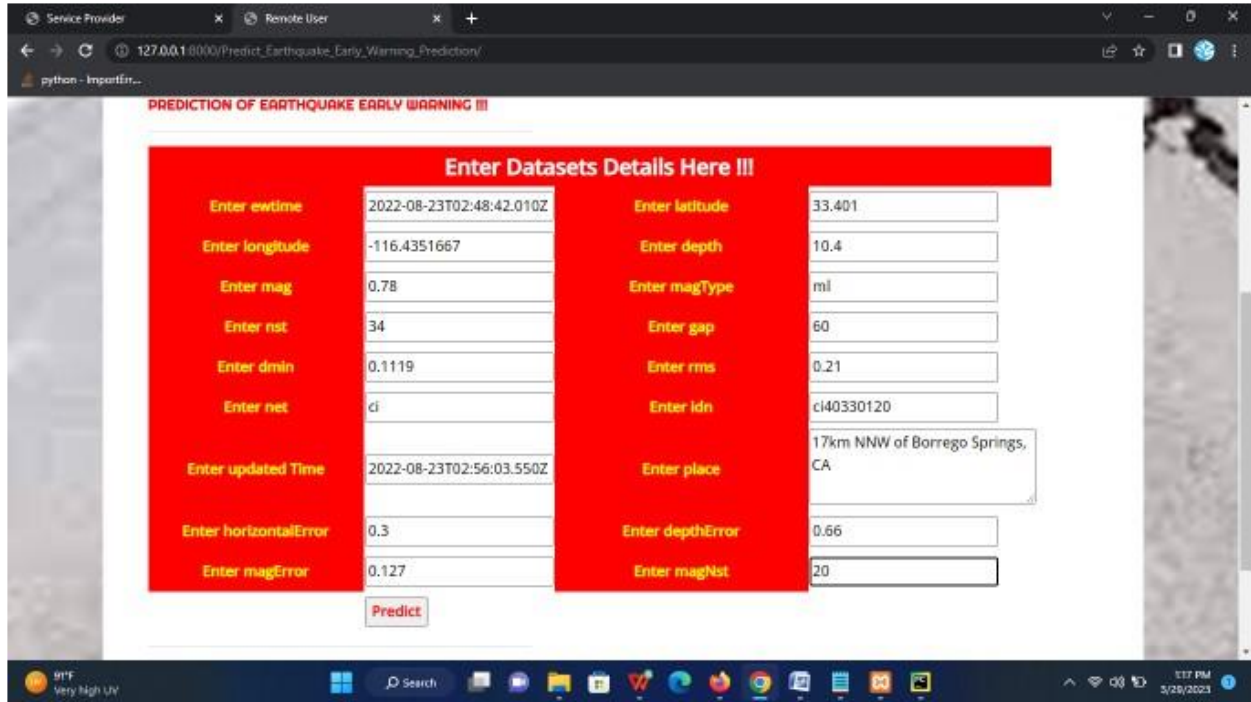


Fig: Enter Values for Prediction

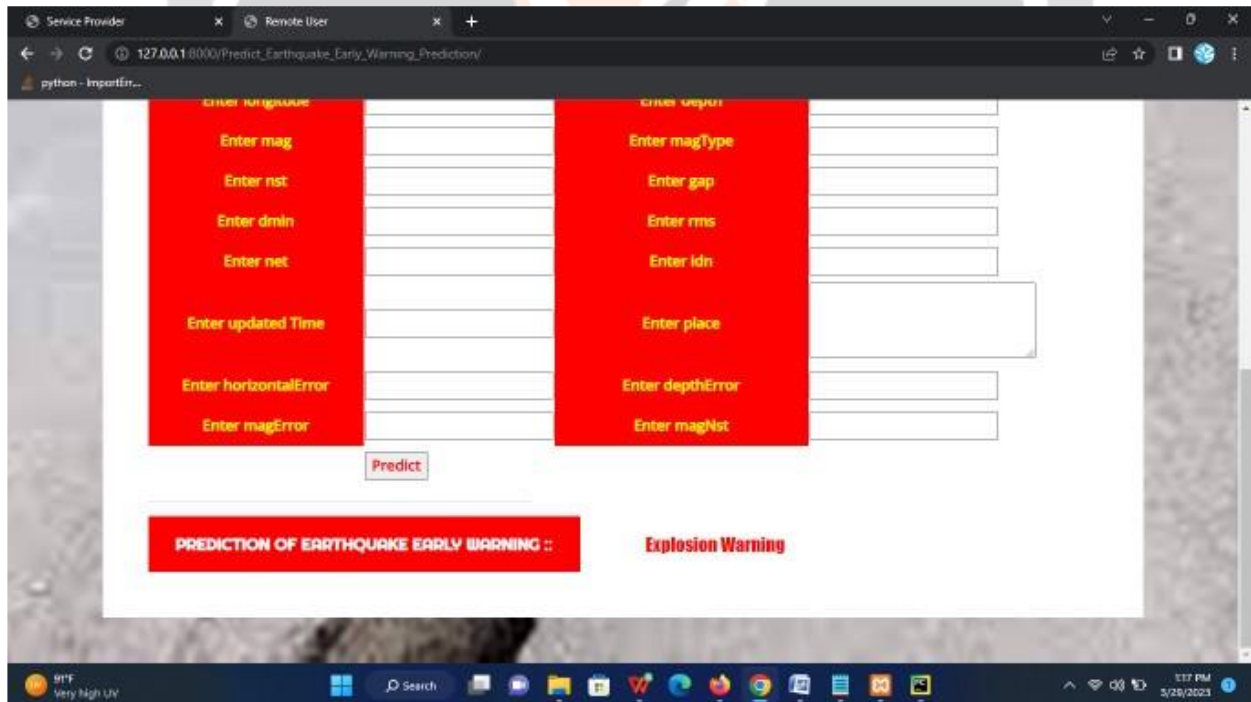


Fig: Prediction Result

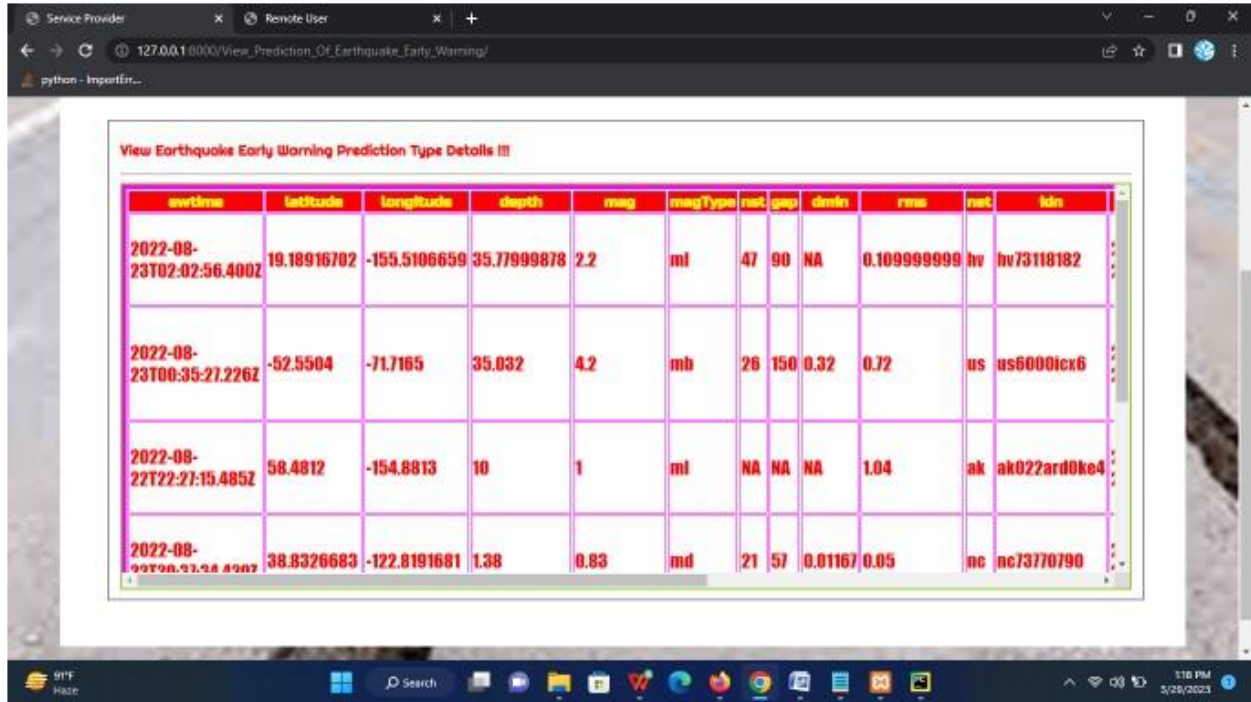


Fig: Earthquake Early warning Prediction Type Details

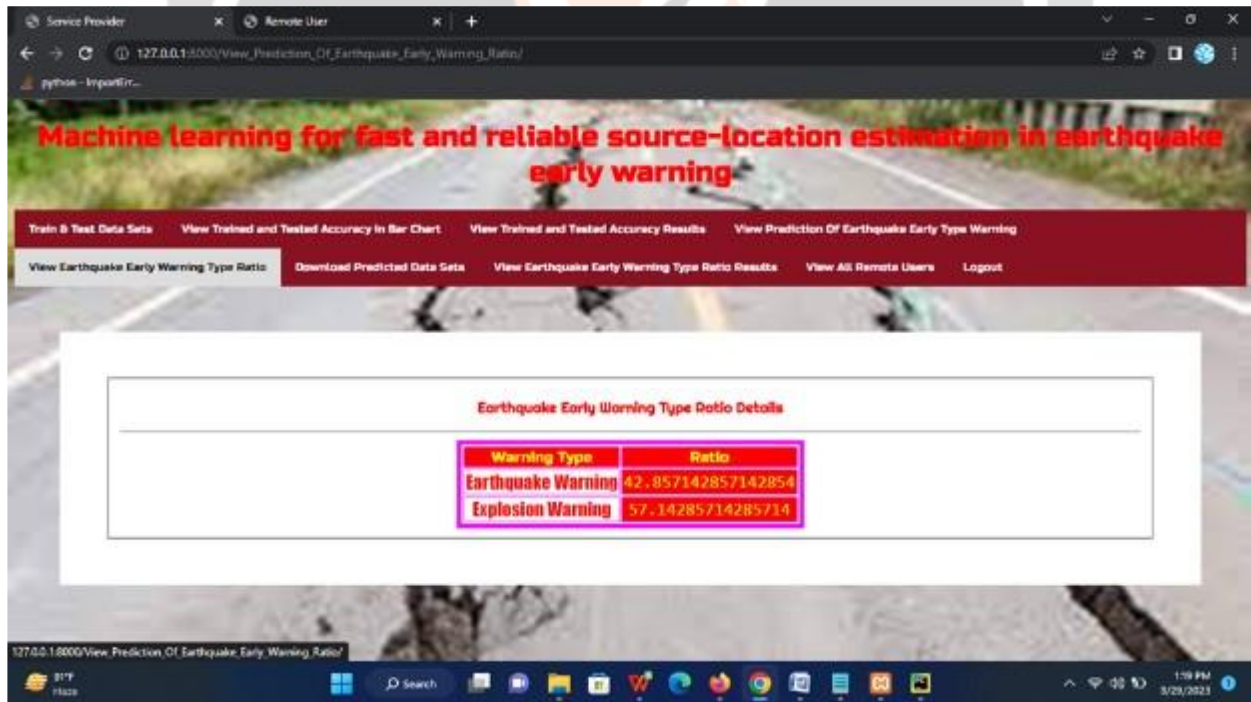


Fig: Earthquake Early warning Type Ratio Details

6. 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.

7. REFERENCE

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