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EARLIER DETECTION OF EARTHQUAKE ESTIMATION OF GEOGRAPHIC LOCATIONS USING NEURAL NETWORK

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A B S T R A C T:

Eaerthquake 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. 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 locationsThe 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. 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

Keywords:Earthquake Early Warning (EEW) system; Machine learning; Earthquake Location.

INTRODUCTION

EARTHQUAKE hypocenter localization is vital in seismology, with applications including tomography, source characterization, and hazard assessment. This emphasizes the significance of having reliable earthquake monitoring systems to precisely determine event origin times and hypocenter locations. Furthermore, the quick and reliable characterisation of active earthquakes is an important, albeit difficult, task for creating seismic hazard reduction tools such as earthquake early warning (EEW) systems.While traditional approaches for designing EEW systems have been widely implemented, it remains difficult to locate hypocenter locations in real time, owing to inadequate information during the early stages of earthquakes. Among the various key aspects of EEW, timeliness is an important consideration, and more efforts are needed to improve hypocenter location estimates with limited data from the first few seconds after the P-wave arrival and the first few seismograph stations triggered by ground shaking. The localization problem can be handled by analyzing a sequence of detected waves (arrival times) and the locations of seismograph stations induced by ground shaking. Among numerous network topologies, the recurrent neural network (RNN) can precisely extract information from a sequence of input data.This method has been studied to increase the performance of real-time earthquake detection and source classification. Several other machine learning-based seismic monitoring systems have been presented. Traditional machine learning algorithms, such as nearest neighbour, decision tree, and support vector machine, have also been compared for earthquake detection. However, one common difficulty with the aforementioned machine learning-based frameworks is that the selection of input features frequently necessitates expert knowledge, which may impair the accuracy of these methods. Convolution neural network-based clustering approaches have been used to regionalize earthquake epicenters and predict their specific hypocenter positions. In the latter situation, numerous stations' three-component waveforms are used to train the model for swarm event localization. In this paper, we present an RF-based approach for locating earthquakes utilizing differential P-wave arrival times and station locations. The suggested technique is only based on the Pwave arrival timings detected at the first few stations. Its timely response to earthquake first arrivals is important for quickly broadcasting EEW signals.

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.

Disadvantages:

- An existing system method is not investigated to improve the performance of real-time earthquake and classification of source characteristics.

PROPOSED SYSTEM

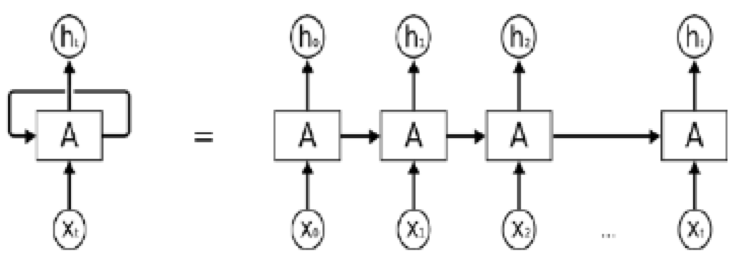
The system proposes a RF-based method to locate earthquakes using the differential P-wave arrival times and station locations (Figure 1). The proposed algorithm only relies on Pwave arrival times detected at the first few stations. Its prompt response to earthquake first arrivals is critical for rapidly 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.

- 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.

RESEARCH METHODOLOGY

The LSTM RNN model proposed in this study includes two hidden layers with 40 hidden units each that are LSTM cells. The backpropagation through time is limited to 15 steps. A dropout layer is included between the 2 hidden layers for regularisation [21]. It will randomly exclude 30% of the activations of the previous layer from propagating to prevent overfitting. The Root Mean Square (RMS) loss is reduced using the Adagrad algorithm which increases the learning rate for more sparse parameters and decreases the learning rate for less sparse ones. This strategy often improves convergence performance over standard stochastic gradient descent in settings where data is sparse [22]. The initial learning rate is taken to be 7 and is exponentially decreased when the RMS loss does not improve for more than 10 epochs. The training was stopped after the loss started to fluctuate despite very low learning rate. The number of epochs came to be 1600. These parameters were selected after trying out other architectures.



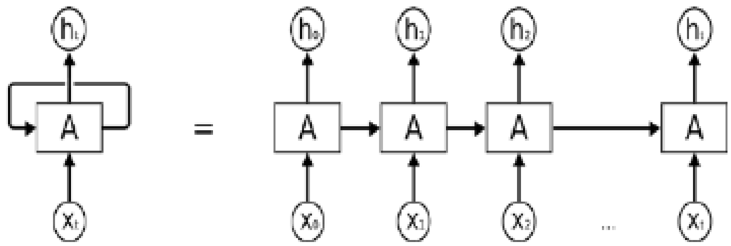


Fig: LSTM RNN architecture

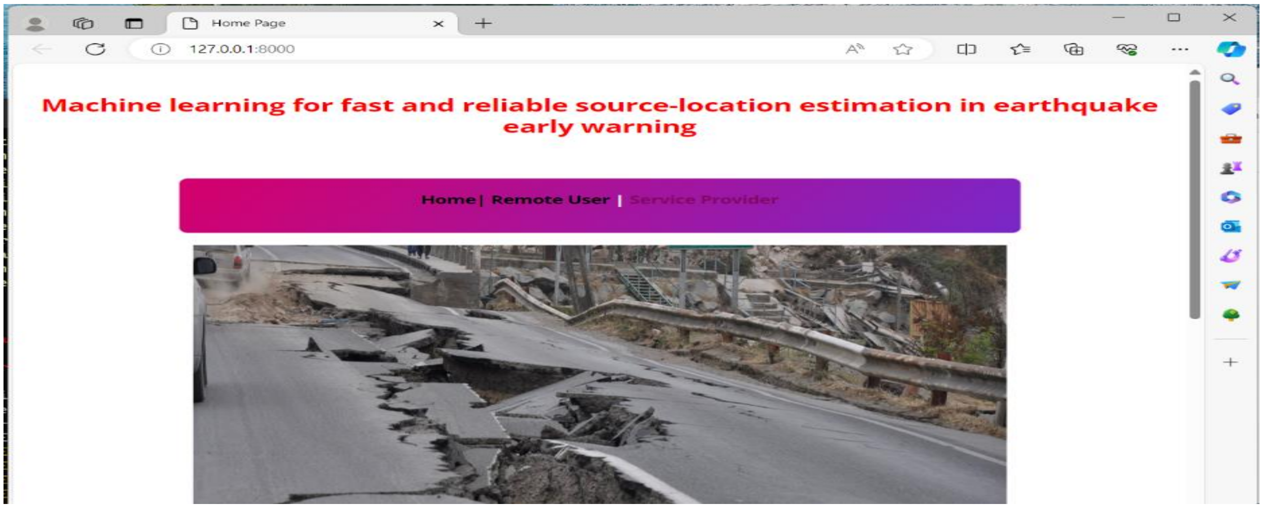


Fig: Home Page

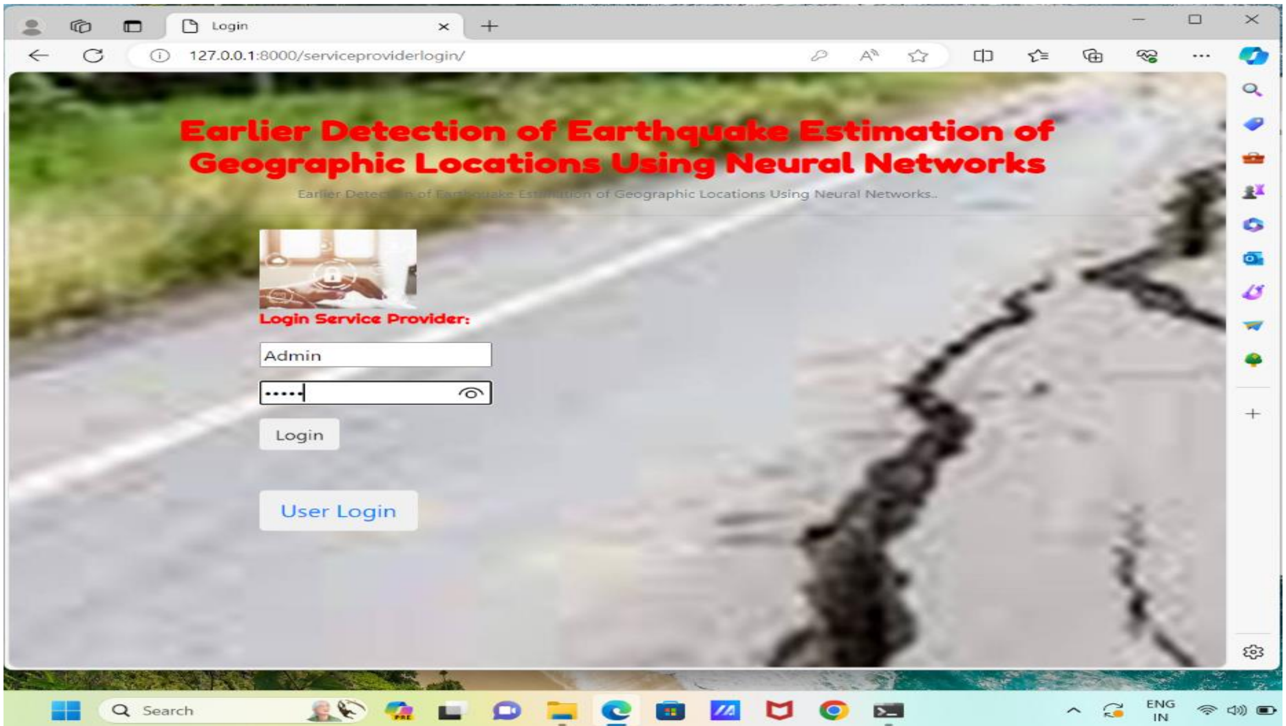


Fig: Login Service Provider Page

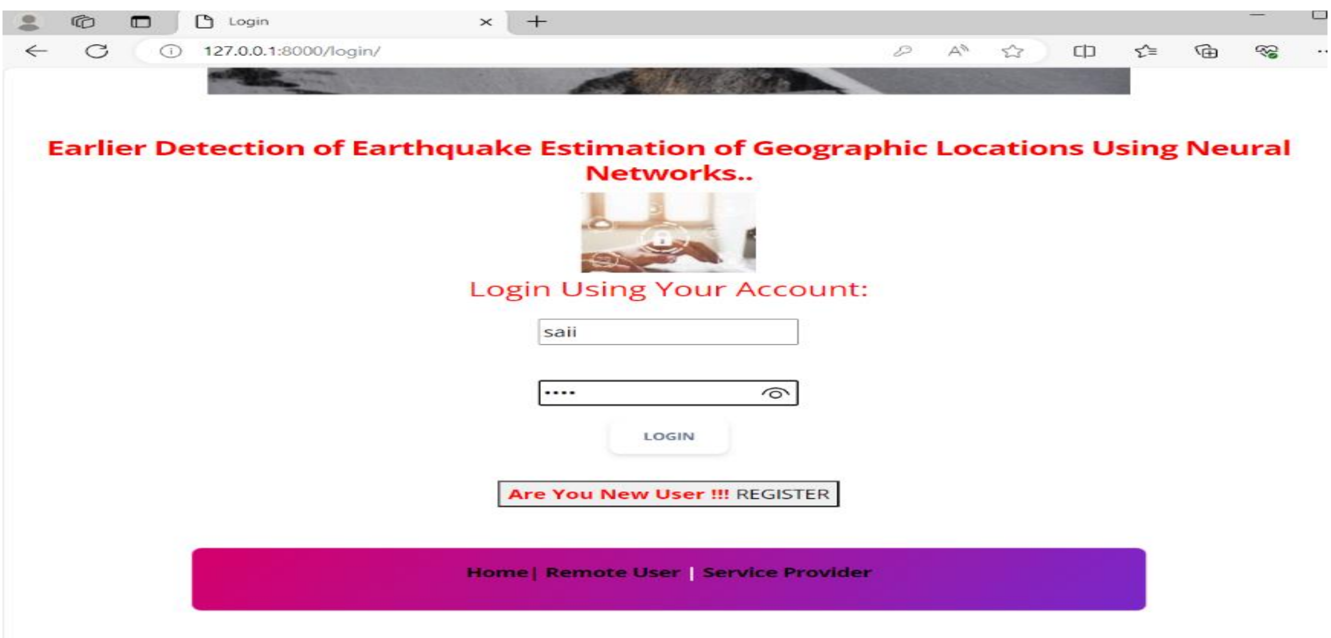


Fig: Login for Remote User

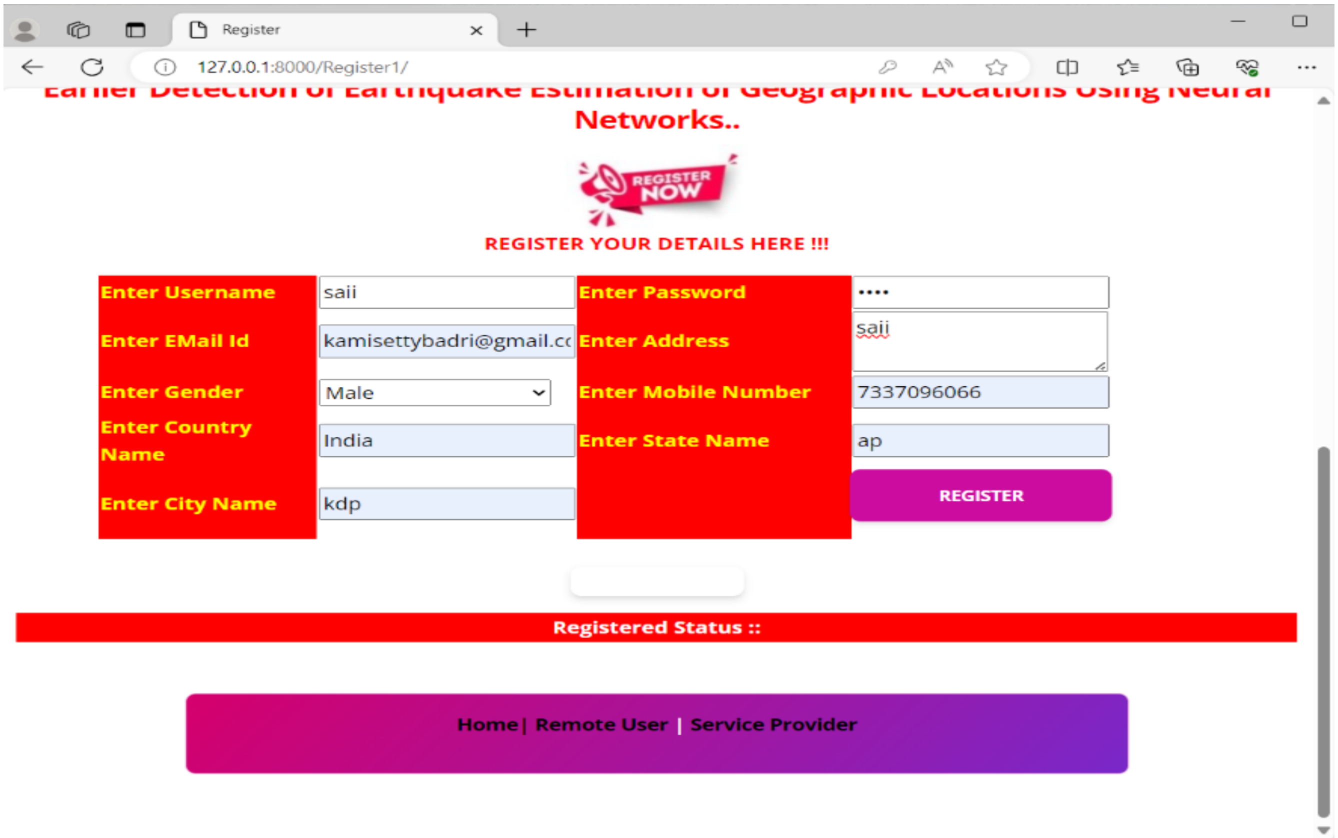


Fig: Registration Page for Remote User

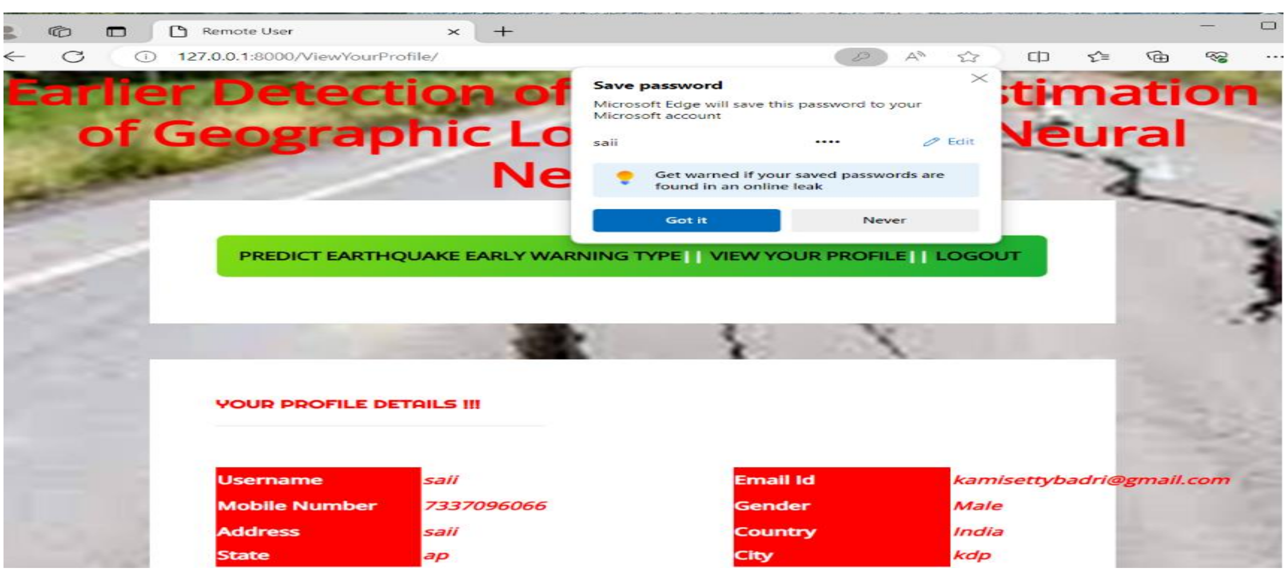


Fig: Remote User Profile Details

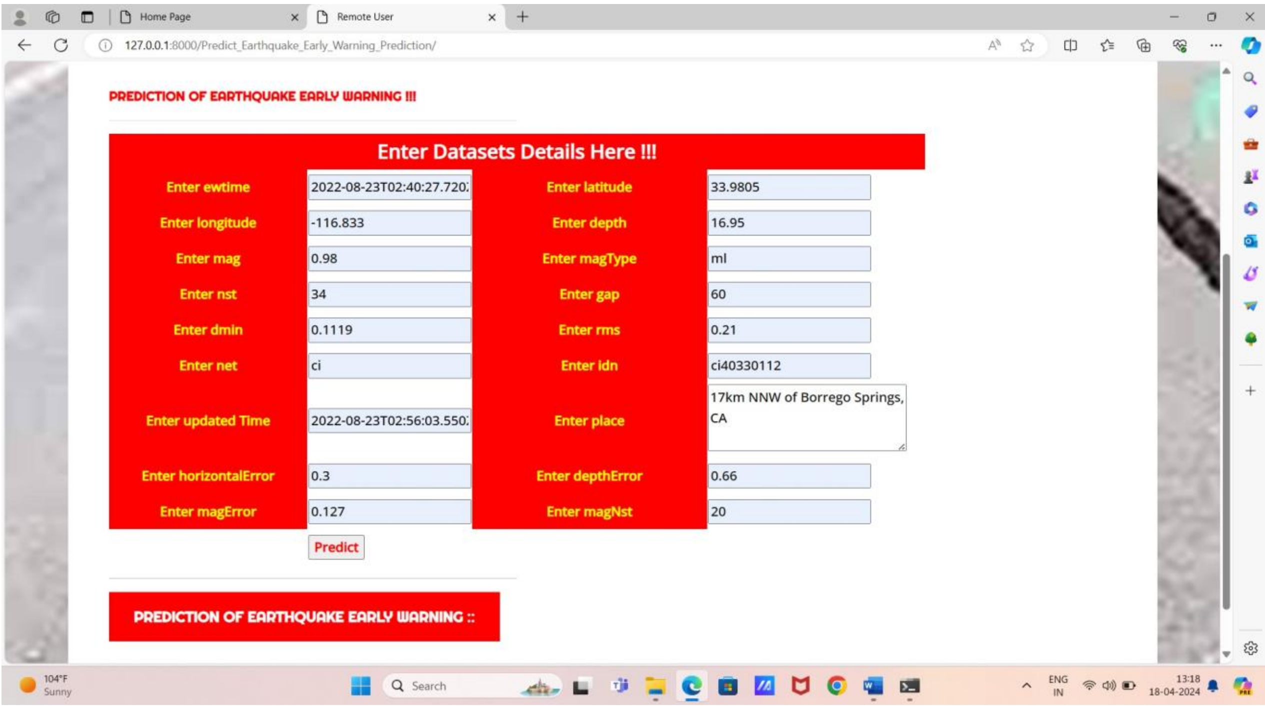


Fig: Enter Details for Prediction of Early Earthquake Warning

Fig: Prediction of Earthquake Early Warning Explosion

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