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Convolutional Neural Network for Earthquake Ground Motion Prediction Model in Earthquake Early Warning System in West Java

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Abstract: As urbanization continues, more people and infrastructure are concentrated in areas that are at risk from earthquakes. This can increase the potential damage and loss of life when earthquakes occur. Indonesia is a region that is near the boundary of three major tectonic plates which has a very high frequency of earthquake occurrences. Over the past two decades, a new approach to earthquake disaster risk mitigation has emerged. It is based on the advent of digital seismology and advances in data transmission and automatic processing that make it possible to send warnings before the largest ground motion that called the Earthquake Early Warning System (EEW). On-site EEW is a type of EEW that consists of limited seismic stations located at a specific destination/infrastructure (for early detection systems). On-site EEW estimates ground motion parameters directly from the characteristics of seismograms recorded by the system. An artificial intelligence approach to EEW is necessary to increase the speed and accuracy of information, which increases processing time, especially in areas very close to the epicenter.

Keywords: Earthquake; EEWS; Machine learning; CNN

Introduction

As urbanization continues, more people and infrastructure are concentrated in areas that are at risk from earthquakes. This can increase the potential for damage and loss of life when earthquakes occur. Indonesia is a region that is near the collision boundary of 3 of the world's major tectonic plates which has a very high frequency of earthquake occurrences (PusGen, 2017).

West Java is Indonesia's most populous province with over 48 million people in 2021. The region's high population density means that any potential earthquake could cause significant damage and loss of life. The region is located near several active faults and tectonic plate boundaries, which increases the risk of earthquakes. In the event of a major earthquake, the high population density in West Java could make it difficult for emergency responders to reach and provide assistance to those in need. Earthquake occurrences are in areas where plate collision boundaries are known as subduction zones and areas that have local faults. Major earthquakes have occurred in the south of Java subduction, including earthquakes with a Mw 7.8 in Pangandaran in 2006 which caused a lot of damage. In 2009, a magnitude 7.6 earthquake struck off the coast of West Java, triggering a tsunami that caused significant damage and loss of life. More than one thousand people were killed, and many more were injured or displaced. In 2018, a magnitude 6.4 earthquake occur, causing damage to buildings and infrastructure in the region. Several people were killed, and many more were injured. Mw 6.6 in Banten in 2022 which caused a lot of damage. In the other hand, in October 2015, Indonesia and China developed High Speed Railway project, which is expected to cover a distance of approximately

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150 kilometers (93 miles) and reduce travel time between Jakarta and Bandung from around three hours to just 45 minutes. The project has faced several challenges, including issues related to environmental concerns including earthquakes potential on the railway area. The Indonesian government has been working to improve earthquake monitoring and preparedness in the region, including the installation of early warning systems and the development of evacuation plans. However, as with any seismic activity, earthquakes remain a serious threat in West Java and the surrounding areas, and it is important for residents and visitors to be aware of the risks and to take appropriate safety measures.

With modern theoretical and computational developments and improvements, the warning time of warning system has evolved from a few minutes to a few seconds after an earthquake, which enables sending earthquake information before the peak motion of the earthquake. This procedure is called the Earthquake Early Warning System, or EEW/EEWS, and is currently one of the most practical and promising approaches to reducing damage from large earthquakes. The approach to artificial intelligence methods in the context of EEW has been carried out by previous researchers including to making the waiting time even greater, especially in areas that are very close to the epicenter. In this paper the authors try to compile a literatur review that focuses on on-site EEW based machine learning model that can estimate the potential for shocks to provide a warning at the location.

Method

In this study, a critical analysis of literature reviews from several publications of national and international journal as well as available archives is carried out. The method used includes several stages. First, search for publications and archives related to the topic. Furthermore, a critical analysis is carried out by correlating several literatures to find concepts to analyze and identify gaps in the formulation of the problem. It is hoped that from this critical study new topics will emerge for further study.

Result and Discussion

The change in the subduction pattern from oblique convergence in Sumatra to southern Java results in different structural patterns and seismicity characteristics between Java and Sumatra. Seismicity records in the subduction zone on Java show that Java is more 'calm' than Sumatra, although large earthquakes that have resulted in tsunamis have also occurred in the Java region, including the Mw 7.8 earthquake in East Java (Banyuwangi) in 1994 and Mw 7.8 in West Java (Pangandaran) in 2006 (Ammon et al., 2006). Apart from the south of java subduction zone, shallow earthquakes originating on the mainland have also frequently occurred in Java in the last few decades. Due to the density of population in Java, these earthquakes had quite a devastating impact. Mapping of earthquake sources in Java, especially active faults that are on land, is currently gaining attention (Marliyani et al., 2016). Marliyani uses various geological methods including mapping, qualitative and quantitative analysis of tectonic geomorphology, and paleoseismology to identified active faults in Java (on shore). Research results show the combination of fault systems, earthquake distribution, geodetic measurements, surface expression, and geological studies in Java suggests that active deformation is accommodated by structures with a small distribution (ranging from kilometers to tens of kilometers) along with a fairly wide distribution. This combination reflects the complex nature of the tectonic processes and structural elements involved in the deformation of the Java region.

Major earthquakes have occurred in the subduction zone area of western Java, including an earthquake with a Mw 6.6 in Banten in 2022 and a Mw 7.8 in Pangandaran in 2006 which caused a lot of damage (Hanifa et al., 2014) Based on various literary sources, earthquake sources in the West Java region; South Java Subduction Zone (Listyaningrum et al., 2017) the Lembang Fault type left-lateral strike slip along 29 km with a potential magnitude of Mw6.8 (Afnimar et al., 2015), Cimandiri which consists of 6 segments with a length of 100 km with maximum earthquake energy potential of Mw6.5 – 6.9, Baribis Fault (Damanik et al., 2021).

Earthquake Early Warning in Disaster Mitigation Efforts

Earthquake mitigation efforts are carried out in 2 ways, long term efforts and short term efforts. In general, the long term effort is to calculate the potential hazard of earthquake disasters using the PSHA (Probabilistic Seismic Hazard Analysis) and DSHA (Deterministic Seismic Hazard Analysis) methods where the PSHA method is an analysis technique for earthquake occurrences for certain birthday periods by making probabilities (or probabilities) with numerical weights from various earthquake sources (Puteri et al., 2019). Meanwhile, the DSHA method takes into account the earthquake hazard from one predetermined earthquake source. Uncertainty can be in the form of uncertainty in the size, location, and frequency of earthquakes that affect the parameter values in the analysis (Iervolino et al., 2006).

Short-term efforts are earthquake predictions, but so far earthquake predictions are not possible (Panza, 2001). Therefore, new approaches to short-term risk mitigation have evolved over the last two decades, based on the emergence of digital seismology and advances in communications and automated processing. This new paradigm is based on the concept of a real-time seismic information system, where seismic stations are interconnected and automatic processing produces fast and accurate information on seismic parameter data (location, time and magnitude) and ground movements. With theoretical and computer developments and improvements, the reporting time of this system has advanced from a few minutes to a few seconds after an earthquake, enabling earthquake warnings before the peak of the earthquake. This procedure is called the Earthquake Early Warning System (EEWS) and is currently one of the most practical and promising approaches to reducing damage from large earthquakes. (Nakamura et al., 2011).

Recent Developments in EEW

In several countries the development of EEW was triggered by the presence of very large victims such as the 1985 M8.1 Mexico City earthquake which caused 20,000 victims and it turned out that there was a 1 minute time difference from the time the first sensor recorded until the strong shaking in Mexico City. Based on this, the development of EEW in Mexico City began in 1991. The Kobe M6.9 earthquake in 1995 that caused 600 casualties was the start of EEW development in Japan. In 2008 the M7.9 Wenchuan earthquake that caused 70,000 casualties was the start of EEW development in this region. One example of successful EEW was the 2011 Tohoku earthquake, warnings were successfully sent to potentially affected areas. The success of EEW in Japan initiated the United States to apply EEW to public information. The 2018 Puebla M7.1 earthquake in central Mexico also successfully provided early warning and provided progress on EEW. Allen et al. reviewed countries that have implemented EEWS, namely Mexico (Suárez et al., 2021), Japan (Doi, 2011), Taiwan (Hsu et al., 2013), Romania (Allen & Melgar, 2019) and Turkey. Some countries are still in the experimental and testing phase: such as: ElarmS in California US, Switzerland (You-Jing et al., 2022) PRESTo in Southern Italy (Brondi et al., 2015), China (Zhu et al., 2019), India (Satriano et al., 2011), Chile, Costa Rica, El Salvador, Nicaragua.

Concept of Earthquake Early Warning (EEW)

Literature reviews from several publications of national and international journal as well as available archives, the hypothesis of EEWS is that the initial P-wave contains information about the magnitude of the earthquake event, which can be used to determine the maximum ground motion of an earthquake.

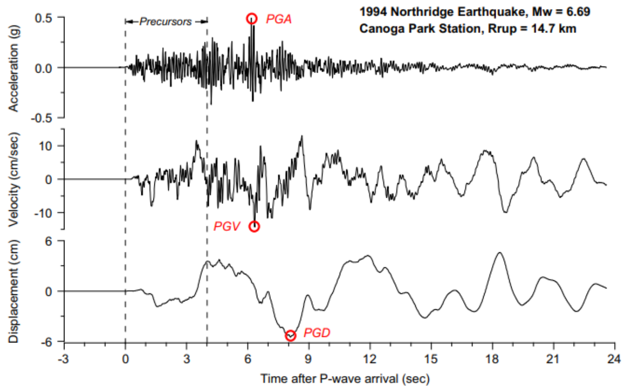

Figure 1. Illustration concept of EEW (Panza, 2001)

The warning time ranges from a few seconds to a few minutes depending on the distance between the user and the epicentre (Cremen & Galasso, 2020). Based on this hypothesis, early studies built a variety of empirical models to estimate the magnitude of the maximum vibration that occurs after the first vibration is detected. EEW systems utilize data from multiple seismic stations located in a region to detect and analyze earthquakes. By gathering data from various stations, these systems can provide more accurate estimates of source parameters such as the earthquake's magnitude and location. They take advantage of the fact that seismic waves travel at different speeds, allowing them to estimate the size and location of the earthquake more precisely (Wu & Kanamori, 2005; Zollo et al., 2014).

Similarly, Kuyuk et al. states that while the onsite-EEW processes P-waves in real time with telemetry latency, the regional EEWS waits three to eight seconds before issuing an emergency alert. During this time, secondary/transitional waves (S), which carry destructive energy and are slower than P waves, have already reached the surface of the Earth and the vicinity of the epicenter. Consequently, a blind spot region occurs where no EEW data are available (Huseyin Serdar Kuyuk & Allen, 2013).

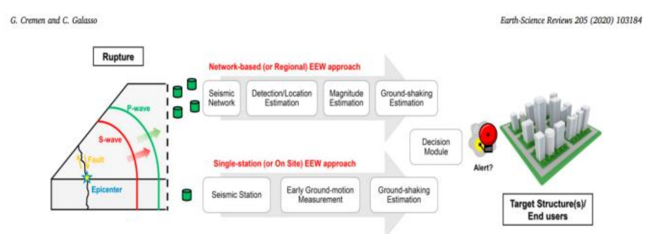

Figure 2. Regional and on-site EEW (Cremen & Galasso, 2020)

Based on the method and the number of sensors involved in the calculation, there are 2 types of EEW, regional-EEW involving many sensors and on-site EEW using only 1 sensor. Both types have complementary advantages and disadvantages. The Regional EEW system consists of a network of seismic sensors located within the predicted epicentre or high seismicity area of a region, to estimate source parameters. These estimates are used to predict ground shaking at locations (Satriano et al., 2011). On-site EEW systems consist of a limited number of seismic stations located at a single point or at several adjacent site-specific sites/infrastructure (front-detection systems). These systems estimate earthquake sources and parameters directly from the characteristics of seismograms recorded by the system (Zollo et al., 2010). While regional EEW systems offer more accurate estimates of source parameters, on-site EEW systems excel in providing faster warning times for locations close to the earthquake source. Both types of systems have their own strengths and are important for earthquake early warning and mitigation efforts (Kanamori, 2005).

Machine Learning in EEW

In the development of many variations of data and methods for estimating PGV (magnitude), PGA and PGD with initial P wave data, as was done by Gunawan et al. (2013) obtaining an empirical relationship between PGA and PD3, (Serdar Kuyuk & Susumu, 2018) using a combination of data waveform, filtered data, absolute data and cumulative data from ground acceleration data, (Wang et al., 2013) using multiple regression combinations of PD1, PD3, PD4 and PD5, (Colombelli et al., 2015) using the weighting of the variables Pd, Pv and Pa, the mean of τp max and Pd for estimation of Magnitude.

Along with the development of science in seismology, approach of artificial intelligence methods is starting to be applied, this is to face the 3V (Volume, Variety, Velocity) challenge where seismic waveform data continues to grow and increase (volume), and the variety of data will also increase, not only seismic data, data relevant to the geophysical field will also develop, for example, the Global Positioning System (GPS) in the form of timeseries and Interferometric Synthetic Aperture Radar (InSAR) in the form of images, and also velocity, which is related to the speed in processing and distribution in real time for earthquake detection. (Anggraini et al., 2021; Cianetti et al., 2021; Jozinović et al., 2020; Lomax et al., 2012; Manley et al., 2022; Muhammad Atif et al., 2022; Seydoux et al., 2020).

Where one method that is reliable enough to perform object information to make predictions, the classification is Convolutional Neural Network (CNN). Where CNN is the development of Multilayer Perceptron (MLP) which is designed to process two-dimensional data. CNN can represent all input information that will be studied so that it can provide good performance and accuracy.

CNNs employ convolutional layers, pooling layers, and fully connected layers to extract and process visual features in a hierarchical manner. Convolutional layers apply filters to the input image, detecting local patterns and features. Pooling layers downsample the feature maps, reducing spatial dimensions while retaining important information. Fully connected layers then perform classification or regression based on the extracted features. CNNs have achieved remarkable success in image recognition, object detection, and other computer vision tasks. They have been widely applied in various domains, including autonomous driving, medical imaging, and facial recognition, among others. However, it's important to note that CNNs are just one type of deep neural network architecture, and there are other architectures such as recurrent neural networks (RNNs) and transformer networks, each with its own strengths and applications (Ayodele, 2010). In seismic data, CNN is used for various purposes such as classification of local earthquakes and volcanic tremors (Takahashi et al., 2021), geological hazard models (Ma & Mei, 2021), wave phase detection and location estimation (Mostaf et al., 2020; Perol et al., 2018; Ross et al., 2018), earthquake clustering (Kriegerowski et al., 2018).

In the EEW case, several studies using deep learning methods to solve EEW problems are; Kuyuk, H. S. and O. Susumu use of 1 second data seismic for processing that makes the lead time even greater, especially in areas that are very close to the epicenter. The use of 1 second data is an advantage of this research because it will create a greater lead time for the user to respond but in this method the features used are still determined by the researcher (Kuyuk et al., 2018). You-Jing Chiang use the CNN method that is very effective in reading features from seismic waveforms with the features used being determined using convolution so that the accuracy becomes higher (You-Jing Chiang et al., 2022).

Jozinović uses a deep convolutional neural network (CNN)-based technique to predict seismic intensity measurements (IM). The input data for the CNN model consists of multi-station accelerated 3C waveforms recorded during the 2016 Central Italy earthquake period for the M 3.0 event. Using a 10-s window of the earthquake onset time, we find that the CNN can accurately predict the IM at stations far from the epicenter that did not record the maximum earthquake. The intensity calculation provides clear information that is easy to understand by the public/user. rather than reporting size scale data or PGA values. So that the response speed of the community is faster.

In another paper, Xiong Zhang proposed earthquake early warning systems that use CNNs and convolutions to detect earthquakes and estimate their source parameters from seismic waveforms. This system determines the location and size of an earthquake as soon as the station receives a seismic signal. This paper demonstrates that CNN can provide correct magnitudes. On-site magnitude data is less effective because it still does not provide information about the level of shocks in the area. Chakraborty proposed using machine learning to detect and calculate the magnitude of an earthquake, resulting in a magnitude error of 0.2 and detection error 0.04 s. This research algorithm of earthquake detection gives very good results (Chakraborty et al., 2022).

EEW is currently one of the solutions in terms of earthquake and tsunami disaster mitigation in the world. Based on a literature review of several national and international journal publications and available archives, and looking at the advantages and disadvantages of various methods, taking into account the earthquake-prone areas in Indonesia, especially in West Java with active land faults, the availability of seismic sensor networks and the direction of EEW development at BMKG institutions, the research theme to be carried out is related to on-site EEW. The use of machine learning to create a model that can estimate earthquake shaking in West Java with the BMKG's accelerometer and intensitymeter network which is currently quite dense is a research opportunity.

Conclusion

EEW is currently one of the solutions in terms of earthquake and tsunami disaster mitigation in the world. Based on a literature review of several national and international journal publications and available archives, and looking at the advantages and disadvantages of various methods, taking into account the earthquake-prone areas in Indonesia, especially in West Java with active land faults, the availability of seismic sensor networks and the direction of EEW development at BMKG institutions, the research theme to be carried out is related to on-site EEW. The use of machine learning to create a model that can estimate earthquake shaking in West Java with the BMKG's accelerometer and intensitymeter network which is currently quite dense is a research opportunity. Then by knowing the development of research as well as the advantages and disadvantages of various methods, the deep learning method with CNN will be chosen, because previous research provides very good accuracy.

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Author Contributions

Sastra Kusuma Wijaya, Nuraini Rahma Hanifa contributed to the design and concept of the research. Melki Adi Kurniawan contributed to the analysis of the results and to the writing of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

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