Earthquake Early Warning System Utilizing an CNN-LSTM-TL Based Method for Detection and Parameters Classification

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***Abstract* –The obvious first line of protection against powerful earthquake motion is to reinforce houses and other structures. The goal of real-time earthquake catastrophe prevention, in contrast to real-time seismology, is to mitigate damage while an earthquake is still underway. A disaster preventive measure that can be put into action in real-time in the event of an earthquake requires an early warning system (EEW). In order to avoid disasters, should not rely solely on EEW. The order of preprocessing, feature selection, and training the model must be meticulously followed. The preparation phase includes data encoding and normalization. Feature selection incorporates principal component analysis and linear discriminant analysis. It utilized CNN-LSTM-TL for the model's training. The results demonstrate a remarkable 96.49% accuracy.**

***Keywords*—Earthquake Early Warning (EEW), Principal component analysis (PCA), Linear Discriminant Analysis (LDA).**

I. Introduction

The main goal of earthquake early warning systems (EEWS) is to provide information about the impending magnitude and timing of earthquakes so that people can take precautions to reduce the damage the system cause. Hence, EEW is an issue that affects society as well as science. If EEW could reduce the impact of future earthquakes and avert many casualties, it would be absolutely astounding. But are the system fair expectations? Can the proposed approach truly expect EEW to reduce earthquake damage that much more easily than previous efforts? Determining whether to alert users, and if so, how, whom, and what kind of warning to provide in a timely manner is the challenge. Despite their high profile and critical importance, these widely shared choices come with substantial technical challenges. But getting effective warnings out to a big audience gets much more difficult. Caution periods for EEWs are significantly shorter compared to those for other dangers. It is common knowledge from past natural disasters that providing prompt, effective warnings is difficult, despite the advantages. Aside from that, the exact procedures to follow are unknown. The rapid and precise shaking estimates provided by the EEW system may not always be sufficient to significantly mitigate the effects of an earthquake, even when used as a warning system. The fundamental goal of PEEW systems is to quickly detect seismic activity and alert the public about the impending tremors induced by S waves. The goal is to reduce the possibility of seismic damage by giving the public a critical evacuation window of opportunity, which can range from a few seconds to dozens of seconds. The number of injuries caused by earthquakes may be reduced by more than half if everyone received seismic alerts and took precautions. In the past decade, PEEW systems have been installed in numerous countries, including South Korea, Mexico, Taiwan, and the United States. Many earthquake-prone locations have seen an increase in public demand for PEEW systems, but their implementation has been hindered by the high initial and ongoing costs. From a risk management perspective, PEEW systems are effective if the system assist decrease risks and avert injuries. The current capabilities and technical performance of PEEW systems have been assessed in a plethora of studies. However, its efficacy with respect to specific Reducing risk can be influenced by social and cultural variables. Everyone involved needs to hear the message, understand it, believe it, and then act upon it. Earthquake early warning (EEW) systems are a feasible method for reducing seismic hazards; the system could reduce the severity of destructive earthquakes. In addition, there are a number of regions where more EEW systems are either being built or tested in real-time. Onsite warning systems and network-based regional warning systems are the two main types of EEW systems. Based on the first P-wave motion of a single station or local array, the onsite warning approach can anticipate the next peak ground shaking at the same spot. However, for a regional warning, scientists make informed assumptions about the location and size of the earthquake's source and predict ground motion in that area based on data collected from seismic networks installed in the area where the earthquake is likely to occur. By setting a P-wave amplitude threshold, sites near the epicenter can receive onsite warnings about approaching ground motion more immediately, regardless of the event's precise location or magnitude. After an earthquake, the first priority should be to assess the damage as soon as possible so that life-saving actions, such securing essential infrastructure, can be implemented. Utilizing earthquake early warning systems (EEWSs) is one encouraging strategy for real-time reduction of earthquake risk. Earthquake Warning Systems (EEWS) are real-time, modern information systems that can swiftly warn of an impending earthquake's possible destructive impacts by analyzing data from dense instrument arrays positioned in the event's source region or surrounding the infrastructure. A crucial component of any EEWS is the capacity to communicate timely earthquake information to potential end users and stakeholders in a flexible, user-friendly, and personalized way. The widespread availability of smartphones and other mobile cell phone technology, as well as wireless Internet connectivity, makes them an excellent choice for receiving broadcast warnings. Many active EEWSs throughout the world are now making use of this technology to report earthquakes, thanks to specialized apps that turn smartphones into seismic detectors or broadcasters. Japan is in the forefront of developing earthquake early warning systems.

II. LITERATURE SURVEY

Early warning systems communicate important information in advance to mitigate the effects of a potentially hazardous event. The importance of early warning systems in mitigating the effects of natural disasters is becoming increasingly apparent[1]. It is thus not unexpected that the system are frequently utilized to transmit warnings regarding floods, tornadoes, avalanches, glacier lake outbursts, debris flows, and tsunamis. This system primarily focuses on their usage in earthquake prediction. [2]Two fundamental ideas form the basis of earthquake early warning (EEW) systems, which aim to notify specified areas (within seconds to minutes) prior to an earthquake-induced ground shaking: In an earthquake, two things happen: first, information travels at a quicker pace than mechanical seismic waves; and second, the bulk of the energy is carried by surface waves and S-waves, which follow the faster but lower-amplitude P-waves. [3]A lot of different parts of society can feel less of an impact from an earthquake within this short warning time? The ability to "drop, cover, and hold on" or, in the event of an evacuation, locate safer spaces within a building, can help individuals survive or at least suffer fewer severe injuries in the event of a disaster. [4]It is possible to prevent injuries by programming lifts to stop at the nearest floor and opening doors; accidents can be reduced by controlling high-speed trains; fires can be prevented by shutting down gas pipelines; and vehicles can be prevented from entering vulnerable structures like bridges and tunnels by switching signals. [5] This is not an exhaustive list, but it does include several important uses that might have access to EEW's advantages. Subsequent notifications, known as post-alert messages, are sent after an initial alert has been sent via numerous channels. [6] Providing post-alert messaging could be crucial for establishing ShakeAlert's credibility and setting realistic expectations among various groups. A communicator's "publics" are the significant audiences with whom the system interact, the people whose interests or whereabouts are fundamental to the message at hand [7]. All three of these categories—receivers, audiences, and communities—are included in the term "publics". Preparation is the key to timely and effective delivery of this message. First, should look at the information needs and expectations of alert recipients based on studies in social and behavioral science. [8] Then, should evaluate the most prevalent circumstances for alert system performance. This will help build effective post-alert communications. After detection, a warning signal will be sent to locations that are vulnerable to shaking. [9] This warning, which may be a mild reminder, could be displayed for a few seconds to two minutes before to the beginning of the shaking. If live close to the epicenter of an earthquake, probably won't get any warning before it hits. [10] In addition, the warning duration and shaking intensity are both affected by the kind of fault rupture that triggers the earthquake. Even if extended warning durations should be possible in theory, many places will likely only get less than 10 seconds' notice of strong shaking. Businesses can reduce the impact of earthquakes with the help of EEWs by implementing automated or procedural solutions. [11] Organizations take actions such as slowing trains, stopping surgeries, or turning off crucial or possibly hazardous equipment. Notifying the public also provides them more time to prepare for danger by leaving dangerous places or by using the "drop, cover, and hold" method. Some studies have shown that EEWs can reduce injuries and even save lives. [12] The United States, Japan, Mexico, and South Korea are among the nations that have EEW systems that are operational. From one country to another, the system is slightly different. A combination of nationwide sensor networks, individual alerting devices, or both is used by several nations. [13] Warnings might come from different places, go through different routes, and say different things depending on the situation in the country. In Aotearoa New Zealand, EEW is still in its infancy because there isn't yet a comprehensive national framework. While various nations have undertaken exploratory studies on the potential public benefit of earthquake warnings, this was far from the norm prior to the development of EEW technology. Because the blind zone is larger when using a long window, short-window analysis is essential so that there is enough time to take the necessary precautions before significant waves come. As can be seen in [14], many scholars have sought to use short-window analysis to distinguish between faraway and close sources. Using a tiny window lowers the accuracy of magnitude estimations, according to[15]. The EEW systems can still send out an alert, nevertheless, despite the reduced accuracy. Deep learning, a state-of-the-art machine learning technique, has recently discovered some use in seismology [16]. Unlike traditional machine learning algorithms, deep learning works with unprocessed data directly. Decomposing input data into many processing layers that represent data with multiple levels of abstraction allows this nonlinear method to better extract relevant features from unlabeled data [17]. Seismic data inversion, [18]lithology prediction utilizing seismic data, and earthquake detection are some of the many proposed uses for deep learning. The classification is based on an 8-second waveform from three stations that end 2 seconds after the most recent P-wave arrival time. [19]Earthquake Early Warning (EEW) feasibility studies and verification of multiple demonstration systems spanned years prior to the launch of the National System for Fast Seismic Intensity Report and its subsequent implementation. The five primary EEWzones were selected from the following locations: the north-south seismic belt in central China, the Beijing capital region (BCR), the coastal areas to the southeast, the center sector of the Tianshan Mountains in Xinjiang, and Lhasa in Tibet. [20]Pilot sites will be chosen to evaluate the system's efficacy before it is fully developed. Some of these locations include the Beijing-Tianjin-Hebei region, Sichuan province, and Yunnan province. The system was supposed to have completed all construction tasks in these areas before officially entering the trial operation stage and providing the public with the early-warning information service. [21] The most current updates to this nationwide EEWS will be the focus of this method. At the outset, the proposed approach will sketch out the general architecture of the system, which includes the most up-to-date standards for generating early-warning information, the design of the software system, and the seismic network that comprises this system.

III. Proposed system

Earthquakes, which are on the rise because to the increasing urbanization of the global population, can have catastrophic consequences on cities located near huge active faults on land or subduction zones offshore. An efficient method for reducing earthquake hazards is Earthquake Early Warning (EEW), provided that cities are in a favorable spatial relation to earthquake sources and that their population is sufficiently trained to react to warning messages. Typically, an EEW system will give an urban area a few seconds to tens of seconds of warning time before the harmful S-wave component of the severe ground motion occurs, in the case that intense shaking is about to occur.

A. Preprocessing:

1) Normalization of Data:

After choosing a dataset, the next step is data cleaning, which entails eliminating noise and standardizing features. Regularization is the process of reducing the dimensions of a dataset to a single range. This is essential due to the fact that the dataset includes values from many scales. A single scale, consisting of one, two, or three digits, is applied to all variables in order to improve the efficiency of machine learning models. This led us to employ minmax normalization. To normalize values inside the range of [0, 1] in this proposed to employ min-max scaling, as shown in Equation (1) below.

$$G_f = \frac{h_f - min(h_f)}{max(h_f) - min(h_f)} \tag{1}$$

where $x = (H_1, H_2, \ldots, H_g)$ represents the number of features. When discussing features in this context, H_f stands for features that require normalizing and G_f for features that have already undergone formalization. This effectively puts all features in the same bucket and gives them equal weights.

2) Data Encoding:

Following the removal of incorrect or duplicate values from the dataset, data encoding was performed as part of this inquiry. Making a numerical value conversion from the nominal features is the following stage [22]. Make sure the backend functions of machine learning models are using integer values before implementing them. This investigation's data encoding process began with the transformation of non-arithmetic data into arithmetic data. Machine learning (ML) algorithms performed backend computations on mathematical values before input was delivered to the proposed model.

B. Feature Selection:

1) PCA:

Specifically, this method was created to represent linear variation in data that has a high degree of dimensionality. Finding two orthogonal basis functions that represent the directions of maximum variation in the data and have coefficients that are decorrelated with each other is the challenge. Principal component analysis (PCA) allows one to find the dimensionality of a linearly embedded manifold and obtain a compact representation. As a means of characterizing face images, it employed PCA using a set of eigenfaces, for short. Given its origins as a robust PCA solution for face detection and recognition problems, Eigenfaces has always been touted as such. Primary component analysis (PCA) is unsupervised and so can be used in place of supervised methods. In order to construct eigenfaces, it utilizes the NN approach, which relies on the Euclidean distance, to classify test vectors. Multilinear Principal Component Analysis The multilinear principal components analysis (MPCA) is a variation of PCA that is basically PCA applied to tensors or multilinear arrays [23]. Simplifying the process would be to locate a multilinear projection for the face image rather than building a 1D vector and then finding a linear projection for the vector. This is due to the fact that every pixel in a facial image is described in two dimensions as part of the multilinear array. Multilinear projection is based on the premise that it can do better than a 1D vector at preserving the association between close pixels.

2) LDA:

As an example, Fisher faces directly employs linear discriminant analysis (LDA) to accomplish face recognition. In LDA, the goal is to locate projection axes where data points belonging to distinct classes are far apart, while data points belonging to the same class should be close together. In contrast to PCA, which uses orthogonal bases to store information in a linear space, LDA stores discriminating information in a linearly separable space using bases that aren't always orthogonal. It is commonly believed that algorithms based on LDA perform better than algorithms based on PCA. Further studies have shown that PCA is less impacted by training data set fluctuations and can outperform LDA even with a limited training dataset. By examining the pixel-to-pixel correlations at a lower statistical level, PCA can be used to discover a set of basis vectors for a collection of face images. It optimizes the variance between pixels to find linear connections. With the pixels serving as random variables and the face images as outcomes, multi-level principal component analysis (MPCA) builds on PCA in an effort to enhance the collection of basis vectors by uncovering higher-order statistical connections between pixels. It is common practice to use NN or a similar algorithm for classification after discovering new basis vectors; this is similar to PCA and LDA.

C. CNN-LSTM-TL Model Training:

A transfer learning mechanism and a CNN with LSTM enable the RUL prediction technique for the cutting instruments. Not only does the provided dataset bolster the proposed approach, but so do the experimental setup and machining parameters. There are multiple distinct steps to the process. Building and pre-training a CNN model with source domain data is essential. Finally, train the model to accurately anticipate the target domain's product deterioration status with the application of a transfer learning methodology.

1) CNN:

a) Pre-Training Stage:

Using the following mapping, the CNN model may learn to convert the input image Y into ground truth data, commonly known as labels X:

$$X = i(Y) = \theta_{CNN}(Y) \tag{2}$$

in which $\theta_{CNN}(Y)$is CNN parameters are used to apply the CNN model function to image Y. The convolutional layers of the CNN model gain feature mappings across several spatial and depth levels of images, allowing it to perform very well when processing images. Since ResNet-18 has a smaller number of parameters and less processing overhead, it is utilized as the basic CNN architecture in this work. In particular, the ResNet-18 architecture's residual connections make it possible to combine specialist feature maps with more general ones in an additive fashion. Furthermore, max pooling procedures enhance the network's learned convolutional features by supplementing certain image regions with the associated max feature value across the pooled area [24]. To train the parameters of the network layer, the proposed approach use back-propagation gradient descent methods. CNNs learn categorical cross-entropy loss during pre-training with the following statements for a mini-batch of G training samples:

$$CE = -\frac{1}{G}\sum_{f=1}^{G}\sum_{d=1}^{G}\Big(Q_{f,d}log(Y_{f,d}) + (1 - Q_{f,d})log(1 - Y_{f,d})\Big) \tag{2}$$

b) Fine Tuning Stage:

As a component of the empirical regression loss metric for tool wear prediction, the MSE loss function is calculated on a mini-batch of G samples. This function measures the divergence of prediction $\hat{X}_f$ from target outputs X_f:

$$MSE(\hat{X}_f, X_f) = \frac{1}{G}(\hat{X}_f, X_f) \tag{3}$$

Given a source domain $\mathcal{J}_p = (Y_p, X_p)$ that uses samples from the source domain and predictions from the source labels, the source job may be described as follows:

$$Q_p: X_p = U_p.Y_p + e_p \tag{4}$$

The parameters (weights and biases) of the CNN model that must be trained for the job at hand are U_q and e_q.

$$Q_q: X_q = U_q.Y_q + e_q \tag{5}$$

The distribution of features is what distinguishes the source domain from the target domain. The source and target domains are thought to be close enough for transfer learning if the expectation of the two distributions, $B(X_p|Y_p) = B(X_q|Y_q)$, are comparable. So, with the help of the CNN's last feature-dense layer, the training loss is regularized using the MMD metric. The algorithm for empirical maximum likelihood divide (MMD) in the domains of interest and source is as follows:

$$MMD^2(Y_p, Y_q) = \left\|\frac{1}{A}\sum_{f=1}^{A}\rho(Y_f^p) - \frac{1}{A}\sum_{f=1}^{A}\rho(Y_f^q)\right\|_{\mathcal{H}}^2 \tag{6}$$

in which $\rho(Y_f^p)$ represents the target feature's embedding and $\rho(Y_f^q)$ represents the source feature's embedding.

Consequently, in order to optimize the distribution difference, an ideal kernel is selected from all possible candidate kernels $\omega \in \omega$. A rich and restrictive kernel is necessary for the MMD to achieve sufficient discrimination between source and target domain features. This proposed used a linear-time approximation due to the enormous cost of computing MMD:

$$MMD_1^2(p, q) = \frac{2}{A}\sum_{f=1}^{\frac{A}{2}} c_v(k_f) \tag{7}$$

where $k_f = (y_{2f-1}^p, y_{2f}^p, y_{2d-1}^q, y_{2d}^q)$ is the quad-tuple definition and $c_v(k_f)$ is the kernel operator:

$$c_v(k_f) = z(y_{2f-1}^p, y_{2f}^p) + z(y_{2d-1}^q, y_{2d}^q) - z(y_{2f-1}^p, y_{2d}^q) - z(y_{2d-1}^q, y_{2f}^p) \tag{8}$$

The MMD statistic is then computed using these feature embeddings. The total loss during CNN training can be explained by combining the empirical regression loss with the MMD regularization:

$$V(Y_p, X_q, \hat{X}, X) = u_1 MSE(X, \hat{X}) + \frac{u_2}{O}\sum_{o=1}^{O} MMD_1^2(p, q)_o \tag{9}$$

where r is the index of the layers that the MMD is computed with regard to, and the metric is calculated for the provided fully connected layer. Then picked u_1 and u_2 from the range [0.8, 0.2] such that u_1 is greater than u_2 and $u_1 + u_2 = 1$.

2) LSTM:

The current output, x_q, can be predicted by an LSTM model by learning the temporal dependencies between the sequential data observations, $y_q, q+1, q+2, q, \ldots$. The LSTM model's prediction and state updating method is controlled by each of the four gates in turn. Oversight (r), input$f$, forget i, and cell candidate n are the four functions that the gate offers. U, R *and* b are the LSTM parameter matrices, whereas the model input weights are $U_r, O_f, O_i and\ O_r$. The biases are $e_f, e_n and\ e_r$. Concurrently, the GRU unit employs three internal methods the reset o_q, the update k_q, and the candidate state $\tilde{c}_q$ to modify the hidden state c_q, which is utilized to calculate the output x_q .

IV. RESULT AND DISCUSSION

Earthquake early warning is the process of getting the word out about when the ground is going to start trembling. One major distinction between EEWs and earthquake predictions is that the ground can detect the nucleation of an earthquake when an EEW is given. To begin, that gather all the data the proposed approach have about the demographics, information needs, and processing capacities of the EEW users.

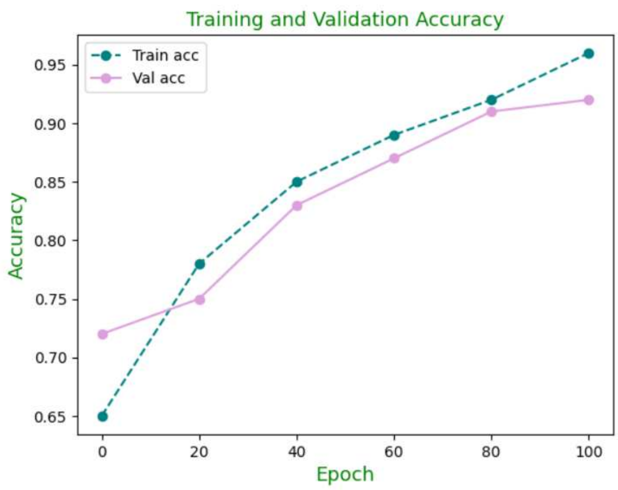

Fig. 1. Training and Validation Accuracy of the model

Figure 1 further demonstrates that the model's accuracy in both the validation and training phases improves as the training step advances. The curves level off after 100 epochs, when the model's accuracy in both training and validation reaches a maximum. This further guarantees that the earthquake early warning system's model is capable of producing reliable forecasts.

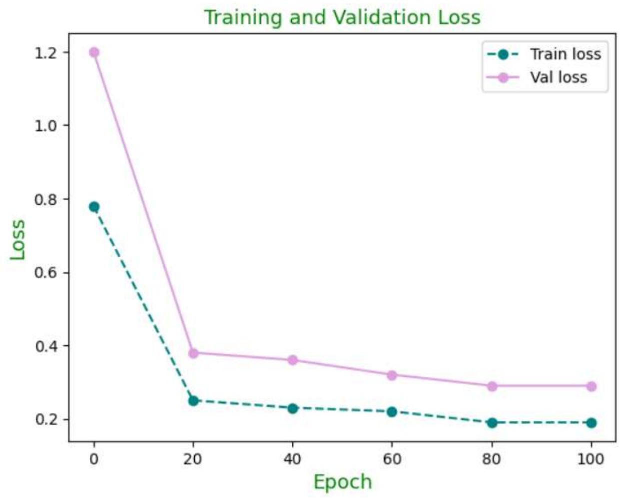

Fig. 2. Training and Validation Loss

Figure 2 shows that as training continue, the model's validation and training losses decrease. As the training step gets closer to 100, the loss function converges slowly.

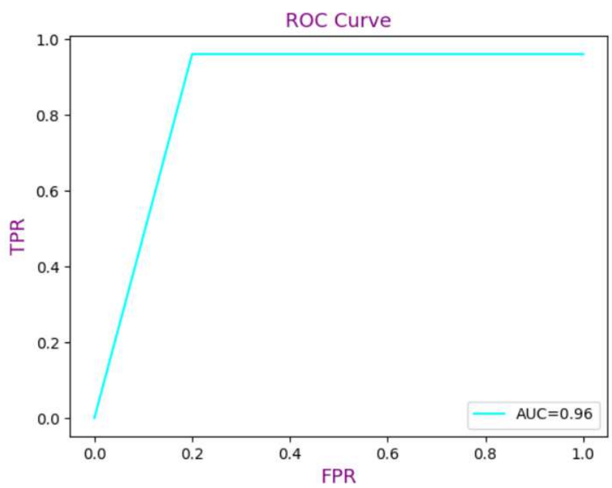

Fig. 3. ROC Curve of Proposed Model

Figure 3 shows the Roc curve of the proposed model. There is little doubt that the proposed model has the potential to provide accurate earthquake early warning system results.

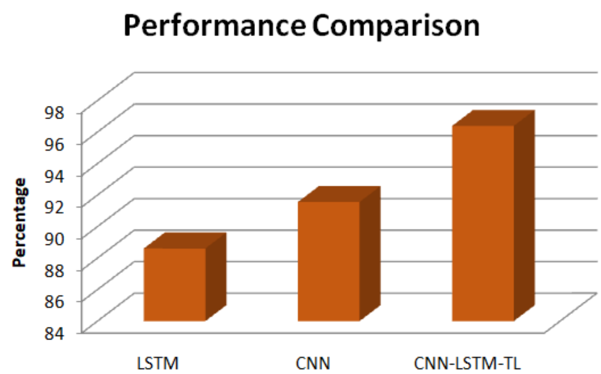

Fig. 4. Performance Comparison

Figure 4 displays the results of comparing the suggested CNN-LSTM-TL model with those of other approaches, such as LSTM and CNN. The LSTM model has the worst validation accuracy (92.58%) out of all of them. An even higher accuracy of 96.49% was achieved with the suggested CNN-LSTM-TL model.

V. CONCLUSION

Earthquake early warning systems (EEW) are a new strategy for developing earthquake- and seismic-hazard resilience in urban areas. Users of EEW systems can receive real-time earthquake alerts, allowing faraway parties (such as governments, communities, and businesses) to take measures before the ground tremors ruin their plans. Workplace accidents and infrastructure downtime are two types of potential losses that EEW systems can help limit. Data encoding and normalization are part of the preparation step. Linear discriminant analysis and principal component analysis are both used in feature selection. All of the model parameters are considered all the way through training using the CNN-LSTM-TL technique. The suggested technique outperforms LSTM and CNN models with an average accuracy of 96.49%.

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