# NARX-Based 1D Convolutional Neural Networks for Enhanced Earthquake Prediction Accuracy

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*Abstract:* - Earthquake prediction is a challenge at this time. This is because the characteristics of earthquakes are very complex and dynamic. This study aims to create a new method that integrates the Non-linear Autoregressive with Exogenous Inputs (NARX) model and 1-dimensional Convolutional Neural Network (1D-CNN) to improve the accuracy of predicting the number of earthquake events in one month. We design the NARX architecture, based on 1D-CNN, to predict earthquake time series data from three different locations in Indonesia: Sunda Strait, South Java, and Bali. The training and testing process was carried out to predict the number of earthquake events in the coming month. The testing yielded the Mean Squared Error (MSE) metric, which demonstrates the good performance of the proposed model. The MSE values for each region of the Sunda Strait, South Java, and Bali are 2.130e-05, 6.018e-02, and 2.524e-02, respectively. The Mean Arctangent Absolute Percentage Error (MAAPE) metric at the prediction stage shows high accuracy in the first month, where the model is able to predict earthquakes in the short term. This research is expected to be able to answer the challenges of earthquake prediction in the field of seismology. Future developments use other deep learning methods for earthquake prediction.

*Key-Words:* - 1D-CNN, NARX, deep learning, earthquakes, time series, prediction.

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## 1 Introduction

The Sunda Strait, South Java, and Bali are areas that have very active geological conditions for earthquake disasters. The Eurasian Plate and the Indo-Australian Plate meet in one of these three locations; this can be indicated by significant geological movements that often trigger earthquakes and volcanic activity, [1].

The geological structure of this region is the subduction of the Indo-Australian Plate under the Eurasian Plate. This subduction is the main generator of earthquakes. The Sunda Strait, located between the Indonesian islands of Java and Sumatra, experiences significant tectonic activity due to the interaction of these major plates, [2].

Southern Java and Bali, located to the east, are part of the Sunda Arc, which extends from Sumatra through Java and Bali continuing further east into the Banda Arc, [3]. The historical seismic record shows that these regions have experienced numerous destructive earthquakes and tsunamis, especially along densely populated and economically significant coastlines. The variability in earthquake occurrences underscores the dynamic and potentially hazardous nature of these regions. The study area, as shown in Figure 1, is divided into three namely, the Sunda Strait, Southern Java, and Bali.


Fig. 1: Tectoning setting in the study regions: (1) Sunda Straits; (2) Southern Java; and (3) Bali, [4]

Traditional methods of earthquake prediction have relied heavily on historical data analysis and the identification of precursor events through various geophysical methods. However, the approach of neural networks has indicated a transformative era in the domain of predictive analytics, offering profound improvements in accuracy and efficiency across a broad spectrum of applications. Several neural network algorithms have become prominent in time series forecasting, due to proficiency in recognizing temporal correlations within datasets. The radial basis function neural network is proficient at forecasting future conditions of chaotic systems, demonstrating significant predictive accuracy. [5].

The use of CNN for time series data especially through adaptation in the form of 1D-CNN, signals a significant innovation in forecasting. In contrast to the 2D versions more commonly used in image processing, 1D-CNN is designed to analyze sequential data, as proven by recent studies. Several studies use the method in predicting time series data such as hotspot prediction of forest fires [6], classification of graphic patterns of financial time series [7], forecasting electricity load profiles 36 hours into the future [8], and earth orientation parameter predictions [9]

The Non-linear Autoregressive with Exogenous Inputs (NARX) model is rooted in a dynamic neural network framework, with an architecture specifically designed to handle feedback systems. [10]. The model's predictive capability is significantly enhanced by the feedback loop established by the addition of previous outputs in the input vector. Several studies use the NARX architecture as a control system to control a hexarotor UAVs [11] and to perform system identification on a DC motors [12]. Then, research on earthquake prediction uses the NARX approach [13] and uses the addition of the deep learning ensemble method [14] to achieve significant accuracy. The purpose of this study is to analyze the performance of the proposed new prediction model by integrating NARX and 1D-CNN features. Earthquake prediction is carried out using three earthquake datasets from different regions to see the consistency by using the integration of the two models.

The writing structure of this research is divided into several parts. Section 2 presents the research methodology used along with describing the stages of the methodology. Where this section explains the dataset used, the NARX model is integrated with 1D-CNN. Furthermore, this section explains the procedure for data preprocessing, the proposed model architecture, the training process, and evaluation using MSE and MAAPE metrics. Section 3 presents the training and testing results for the three datasets and predicts the number of earthquake events for the next four months in each research area. Section 4 is the final part of this paper, which provides a summary of contributions and suggests potential areas for future research.

# 2 Problem Formulation

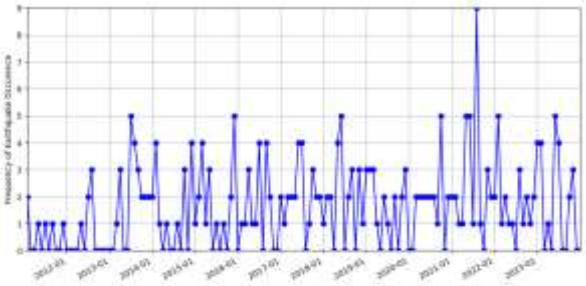
This study proposes a new architecture that integrates NARX and 1D-CNN models to improve the accuracy of a time series prediction of the number of earthquake events. Convolution in 1D-CNN can be useful for capturing hidden patterns sequentially in a data series. While NARX is an architecture that can identify complex and non-linear temporal patterns.

Predicting earthquakes is typically difficult because of the non-linearity of earthquake data and the dynamics that underlie these events. 1D-CNNs have demonstrated significant efficacy in time series classification and forecasting tasks. The one-dimensional convolution operation of convolutional neural networks finds the right internal structure to make deep features from earthquake time series data that is fed into the network. The 1D CNN architecture can dynamically extract features from temporal data.

## 2.1 Data Preparation

The dataset comprised seismic events that occurred in physically significant regions within the Sunda Strait, the southern part of Java, and Bali. More specifically, the dataset was refined to exclusively include seismic occurrences occurring in Indonesia, as reported by the Indonesia Meteorological Climatological and Geophysical Agency (BMKG) that have a magnitude exceeding 4 and a depth below 100 kilometers.

To enrich the model learning base with patterns of previous earthquake events, the dataset was augmented with historical data from the same regions. Furthermore, the data were preprocessed based on the frequency of earthquake events in each month. Figure 2 shows the frequency of earthquake occurrences in the (a) Sunda Strait, (b) Southern Java, and (c) Bali region. The earthquake event dataset, with a length of 156, was then augmented with a standard deviation of 5% to obtain training data with dimensions (156, 1000). Data testing used actual data, and the best model was then used to predict the earthquake activity for the upcoming months.



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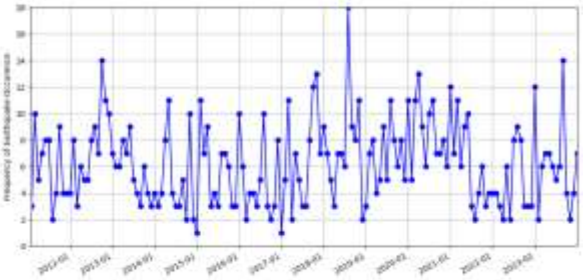

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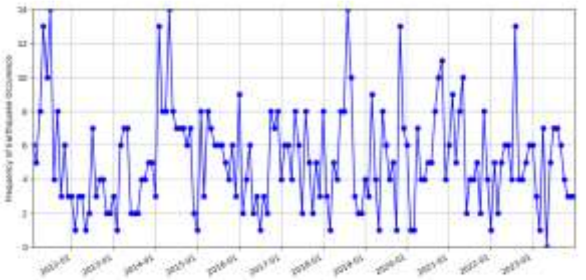


(c)

Fig. 2: Frequency of earthquake occurrence data (a) Sunda Strait; (b) Southern Java; and (c) Bali region

## 2.2 1D-CNN Model

1D-CNN model is a significant adaptation of conventional convolutional neural networks. It is typically used in image processing but has been adapted to handle 1-D data, such as time series. In the field of prediction, the 1D-CNN model excels due to the ability to process temporal sequences by learning from the spatial dependencies within the data. Contrary to traditional time series forecasting methods which may explicitly model the time component, 1D-CNN operates by extracting features from time series segments. The architecture of 1D-CNN is shown in Figure 3.

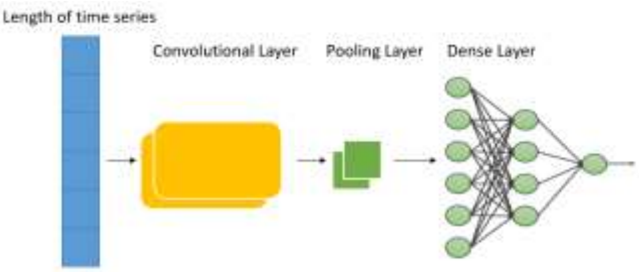



Fig. 3: Basic Architecture 1D-CNN

1D-CNN applies convolution operations to time series data using a sliding window mechanism. This approach helps the model capture local dependencies and patterns within a fixed window or interval, effectively identifying local features that can predict larger outcomes. Each convolution layer applies various filters to the input, producing features that represent different aspects of the data. These features, which may correspond to certain signatures before the event, are then aggregated and averaged to form a feature vector for the final prediction. The basic equation for convolution operations in 1D-CNN is [15]:

$$(x * w)_i = \sum_{j=0}^{k-1} x_{i+j}.w_j + b \qquad (1)$$

Where $x$ is input with length $n$, filter kernel $w$ has length $k$, and $b$ is bias. Furthermore, 1D pooling is usually carried out with operations such as max or average pooling. Max pooling with size $p$ is shown in the equation:

$$y_i = \max\left(x_{(i.p)}, x_{(i.p+1),\ldots\ldots,} x_{(i.p+p-1)}\right) \qquad (2)$$

$y$ is the output of the pooling layer and $p$ is the pooling size. After the pooling layer, we have a 1D array that we will flatten into a 1D vector to feed into the dense layer. Suppose the output of the pooling layer has length $m$. After flattening, we get a vector $z$ has length $m$. The output of the dense layer is:

$$o = f(W.z + b) \qquad (3)$$

Where $o$ is the output of the dense layer, $W$ is the weight matrix, $b$ is bias, and $f$ is the activation function.

## 2.3 NARX Model

NARX is a type of neural network designed for modeling and predicting time series data. It is particularly useful for cases in which future values are not only dependent on past values within the series but also on additional external inputs. In the dimension of time series prediction, NARX model is valuable because it considers past data as well as potentially important external factors when making predictions. The general architecture of the NAX neural network, as shown in Figure 4 follows the equation, [16]:

$$y(k) = f[y(k-1), \ldots, y(k-n_a), \\ u(k-1), \ldots, u(k-n_b)] \qquad (4)$$

Where $y$(k) is a non-linear function $F$ related to the *k-th* Output ($y$) and the *k-th* Input ($u$). Meanwhile, $n_a$ and $n_b$ represents the amount of delay at input and output. NARX model describes the relationship between past input and output which is used to predict current output. The transfer function in this model is Non-linear and represented by the Multi-Layer Perceptron Neural Network (MLPNN) structure. This structure consists of hidden layers and nodes, assigned weights *v* and *w*, respectively. The model predicted output $\hat{y}$(k), is compared to the actual output, *y*(k), to calculate the resulting error.

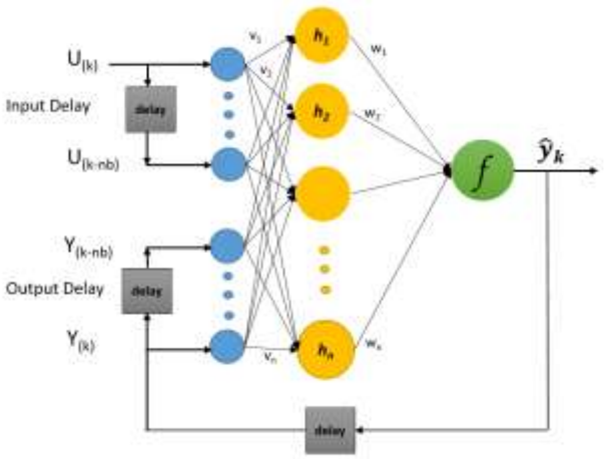



Fig. 4: Architecture NARX

### 2.4 NARX-based 1D-CNN Model

The architecture of the integrated 1D-CNN model was derived from the NARX framework. The input U(k) comprises an earthquake dataset in the form of a time series at time t, which is subjected to an input delay to capture the temporal pattern of the data. The 1D-CNN model then processes the delayed input, extracting features from the temporally structured data in the convolutional layer. The 1D-CNN architecture is based on the NARX model, as illustrated in Figure 5.

Filters in the convolutional layer identify patterns and features at various scales, transforming the input data into a feature-dense representation. The 1D-CNN produces an output, denoted as $\hat{y}$(k), which is the predicted value at time $t$. The delay feature and convolutional processing are quite important parameters so that the model successfully utilizes current and past data to predict future events. This improves the accuracy and reliability of earthquake prediction.

The output of this model is fed back as in the standard NARX model, after being delayed to become input. We continue this step until we reach a specific iteration that yields the best results. The next step of this research involves performing a multi-step prediction. This process is carried out to test the extent to which this model can predict the number of earthquake events in the next few months.

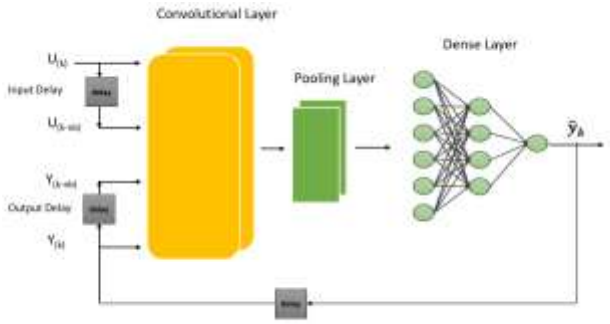



Fig. 5: Architecture NARX-based 1D-CNN Model

Mean Squared Error (MSE) is employed to evaluate predictive models, particularly in time series forecasting, during both training and testing phases.

$$MSE = \frac{1}{n}\sum_{i}^{n}(y_i - \hat{y}_i)^2$$

The Mean Arctangent Absolute Percentage Error (MAAPE) can be applied to evaluate the accuracy of upcoming predictons.

$$MAAPE = \frac{1}{n}\sum_{i}^{n} arctan\left(\left|\frac{y_i - \hat{y}_i}{y_i}\right|\right)$$

The actual values are represented $y_i$ , the predicted value is indicated $\hat{y}_i$ denotes, and the number of observations is denoted by $n$. MAAPE evaluates error within a constrained range, rendering for conversion to a percentage:

$$Accuracy(\%) = \left(1 - \frac{MAAPE}{\pi/2}\right) \times 100\%$$

# 3 Problem Solution

The preliminary training phase applied the data from the Sunda Strait earthquake, following the parameters and framework outlined in Table 1. The next training phase used data from Southern Java and Bali, including structure and architecture as detailed in Table 2 and Table 3.

Table 1. Performance model for Sunda Straits

| Filter | Kernel | Number of Delays | Training MSE | Testing MSE |
|---|---|---|---|---|
| 32 | 2 | 6 | 3.392e-02 | 4.129e-02 |
| 64 | 2 | 12 | 6.673e-04 | 8.810e-05 |
| 64 | 2 | 6 | 2.878e-02 | 6.179e-02 |
| 128 | 2 | 12 | 3.057e-04 | 2.130e-05 |

Table 2. Performance model for Southern Java

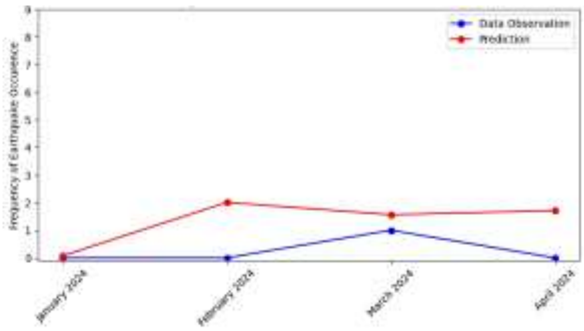
| Filter | Kernel | Number of Delays | Training MSE | Testing MSE |
|---|---|---|---|---|
| 32 | 2 | 6 | 4.119e-03 | 3.837e-01 |
| 64 | 2 | 12 | 2.989e-05 | 6.985e-02 |
| 64 | 2 | 6 | 3.821e-03 | 2.120e-02 |
| 128 | 2 | 12 | 2.985e-05 | 6.018e-02 |

Table 3. Performance model for Bali region

| Filter | Kernel | Number of Delays | Training MSE | Testing MSE |
|---|---|---|---|---|
| 32 | 2 | 6 | 6.955e-03 | 6.639e-01 |
| 64 | 2 | 12 | 9.588e-04 | 3.001e-03 |
| 64 | 2 | 6 | 4.885e-03 | 4.342e-01 |
| 128 | 2 | 12 | 8.028e-06 | 2.524e-02 |

Based on the data in the table, it is evident that across all three regions, the model with 128 filters, a kernel size of 2, and 12 delays consistently outperforms others. The consistent performance across diverse geologic zones indicates the robustness and versatility of this model configuration in capturing the complex patterns necessary for accurate earthquake prediction. Following the evaluation and selection of the optimal model configuration, the next phase of research involves applying this model to predict seismic activity for the upcoming four-month period spanning from January to April 2024. This period was specifically chosen to assess the model's effectiveness in real-time earthquake prediction in the Sunda Strait region, Southern Java, and Bali. Figure 6 presents a comparison between the predicted values for the next four months and the actual data. Figure 6(a) is a graph of the prediction results for the Sunda Strait. The graph shows the agreement between the actual data and the prediction results between January and February 2024; there is a slight decrease between March and April. Figure 6(b) is a graph of the prediction results for South Java. The prediction results show high consistency with the actual data, especially during February and March 2024. Although there is a deviation in April, the model needs further improvement in long-term forecasting. Figure 6(c) is a graph of the prediction results for the Bali Region. The model had a high level of accuracy throughout the months of January and February 2024, with a slight divergence observed in March and April. The overall performance demonstrates the model ability to accurately represent the seismic activity patterns in the Bali region.

Table 4 shows the accuracy of earthquake predictions for each region over four consecutive one-month periods, covering a total forecast range of four months. All regions had high accuracy in the first month, demonstrating the model effectiveness in short-term earthquake prediction. The model achieved a faultless accuracy of 100% for the one-month forecast in the Sunda Strait region. However, the accuracy was significantly reduced in the subsequent months, with a decrease to 70%, 76.67%, and 64.81% for the two, three, and four-month prediction predictions respectively. This trend implies that the model capacity to accurately forecast decreases as the forecast horizon extends, even though short-term predictions are highly reliable.

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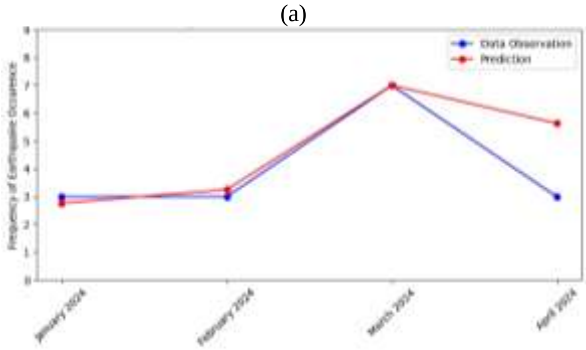


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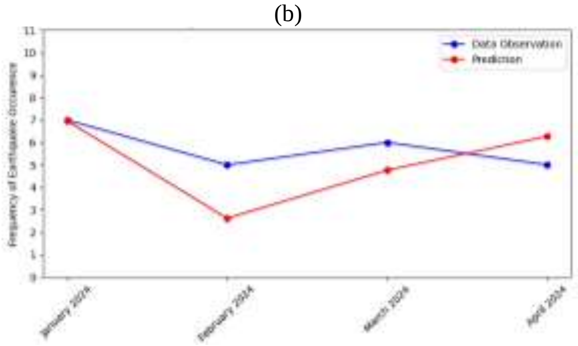


(c)

Fig. 6: Predictions for the next four months consecutively (a) Sunda Strait; (b)Southern Java; and (c) Bali regions

Table 4. Accuracy of predictions for the *n*-months ahead

| Region | Accuracy | | | |
|---|---|---|---|---|
| | 1-Month | 2-Month | 3-Month | 4-Month |
| Sunda Strait | 100% | 70% | 76,67% | 64,81% |
| Southern Java | 97.88% | 97.88% | 98.59% | 87.88% |
| Bali Region | 100% | 87.89% | 88.42% | 88.17% |

The model maintained a high level of accuracy for the first three months in the Southern Java region. A 97.88% accuracy was obtained for both the one and two-month predictions as well as a slight improvement to 98.59% for the three-month. However, there was a significant decrease to 87.88% for the four-month prediction. This suggests that the model is rather effective for three months but accuracy starts to decline after this period.

In the Bali Region, the model demonstrated a flawless accuracy of 100% for the one-month forecast. The accuracy experienced a minor decline to 87.89% for the two-month forecast, followed by an improvement to 88.42% for the three-month. The precision for the fourth-month forecast remained consistently high at 88.17%, indicating that the model consistently performs well for longer prediction periods in this specific region compared to others.

The model showed high accuracy for short-term predictions in the Southern Java region. This high level of accuracy indicates that the model effectively captures the underlying patterns and dynamics influencing short-term variability. The results indicate that the predictive model demonstrates outstanding performance in the short term across all locations. However, the accuracy tends to diminish as the forecast horizon increases. Many forecasting models commonly show this feature due to the growing uncertainty and variability in longer-term predictions. Further studies are needed to determine the regional elements that contribute to the relatively constant performance of longer forecasts in the Bali region.

# 4 Conclusion

In conclusion, the study investigated the efficacy of a fused model that integrated 1D-CNN and NARX for forecasting seismic events in a temporal sequence. NARX-based 1D-CNN model showed a robust capability to capture the temporal patterns necessary for precise short-term earthquake forecasts. Furthermore, the model showed exceptional accuracy within a one-month initial prediction interval throughout the region, with a perfect accuracy rate of 100% in the Sunda Strait and Bali, as well as approximately 98% in Southern Java. The results confirmed the model capacity to effectively manage intricate seismic data patterns and the potential as a dependable tool for predicting earthquakes in the near future.

This study enriches the field by combining 1D-CNN with NARX, producing a model that can better capture non-linear temporal relationships in seismic data compared to existing methods. The integrated model provides a more robust framework for short-term earthquake prediction compared to other studies, which often depend on either statistical models or simply neural network methods. By combining the characteristics of both methodologies, this model offers improved accuracy and reliability.

The accuracy of predictions generally decreased in long-term forecasts, especially after the first month. These trends emphasize the difficulties in sustaining accurate predictions over a long time, which are likely caused by the changing nature of seismic activity and the increasing uncertainty in long-term projections. Future studies should prioritize addressing these problems by integrating supplementary factors, enhancing data quality, and using more sophisticated modeling methods.

**Declaration of Generative AI and AI-assisted Technologies in the Writing Process**

During the preparation of this work the authorsused ChatGPT in order to improve clarity and language. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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**Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)**

- Hapsoro Agung Nugroho was responsible for implementing algorithms in the study.
- Aries Subiantoro focused on refining the optimization algorithms to enhance model performance.
- Benyamin Kusumoputro designed and conducted critical processes for the development of the NARX-based 1D CNN model.

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**Conflict of Interest**

The authors declare that there are no conflicts of interest.