

THE APPLICATION OF THE ARTIFICIAL NEURAL NETWORK (ANN) METHOD FOR FORECASTING THE SOUTHERN OSCILATION INDEX (SOI)

Fathia Syahla Az Zahra^{1*}, Bagus Sumargo², Dania Siregar³, Auria Yusrin Fathya⁴

^{1,2,3,4} Department of Statistics, Faculty of Mathematics and Natural Sciences, State university of Jakarta

Rawamangun Muka Street, East Jakarta, DKI Jakarta, 13220

Corresponding author's e-mail: * fathiaazzahra02@gmail.com

ABSTRACT

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Indonesia's seasons are influenced by global phenomena such as ENSO. This phenomenon affects rainfall intensity in Indonesia through its two main phases: El Nino and La Nina. One method to detect these events is by analyzing the Southern Oscillation Index (SOI). A highly accurate SOI forecasting model is critical for both short-term and long-term development planning, particularly in anticipating future extreme seasons. One of the methods used for forecasting is the Artificial Neural Network (ANN). This study aims to develop an ANN model capable of predicting the SOI index. Based on forecasting using training data, the optimal model architecture identified is 12-7-1, which achieved the smallest MSE value of 0.0095 and a MAPE of 17.6851. With an error rate below 20%, the 12-7-1 architecture demonstrates strong forecasting capabilities. The study forecasts the SOI index for the next 12 months, indicating a trend from negative values at the beginning of the year to more positive values toward the year's end.



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1. INTRODUCTION

ENSO (*El Nino Southern Oscillation*) is a phenomenon involving deviations in sea surface, characterized by warmer or cooler water than normal conditions in the central and eastern Pacific Ocean. ENSO is a *non*-periodic global climate system with two phases, El Nino, and La Nina. El Nino refers to the warm phase, marked by an increase in sea surface temperatures in the equatorial Pacific Ocean, while La Nina is the cool phase signified by decrease in sea surface temperatures in the same region. El Nino can lead to a drop in sea surface temperatures in Indonesian waters, while La Nina tends to cause an increase in sea surface temperatures in Indonesian waters (Kovats, 2000; Xiao & Mechoso, 2009; Luo et al., 2010; Aldrian et al., 2011; Wang et al., 2017; Fitria & Pratama, 2013).

Indonesia is located near the equator, positioned between the continents of Asia and Australia and the Indian and Pacific Oceans. Its equatorial location makes Indonesia's seasonal system influenced by various factors. The onset of the rainy and dry seasons does not occur consistently each year (Tjasyono, 2008). According to Yamagata et al. (2002), this variability is due to Indonesia's seasons being affected by global phenomena such as ENSO.

The ENSO phenomenon influences rainfall intensity in Indonesia. ENSO phenomenon has significant impacts on the climate and oceans, especially in the eastern part of Indonesia (Aldrian & Susanto, 2003). Both climate anomalies, El Nino and La Nina are crucial in shaping the annual climate, typically causing changes in rainfall volume (Hidayat & Ando 2014). In addition to affecting rainfall intensity, ENSO also affects extreme weather, prolonged dry and rainy seasons, and droughts across various regions in Indonesia (Irawan, 2006). If the El Nino phenomenon occurs during the dry season, it tends to exacerbate the impact of drought, and if it happens during the rainy season, it reduces rainfall during that period. Conversely, when the La Nina phenomenon occurs, it generally increases rainfall intensity, both during the dry and rainy seasons (Aldrian, 2002 & 2008; Utami et al., 2011).

One way to detect El Niño and La Niña events is by examining the Southern Oscillation Index (SOI). The SOI represents the difference in atmospheric pressure at sea level between Tahiti (eastern Pacific) and Darwin (western Pacific), which is caused by the temperature differences in the sea surface between these two regions (Zakir et al., 2009).

Climatologists and meteorologists often use the SOI to assess the strength of ENSO. Historical extreme seasonal events in various parts of the world are closely associated with the intensity and duration of the SOI. Developing a highly accurate SOI forecasting model is essential for effective long-term and short-term planning. Especially in anticipating future extreme seasonal changes.

In statistics, one method for predicting the future is forecasting. Forecasting is used to estimate what will happen in the future based on past data. Predictions about the future are made using historical data from a variable, which is referred to as a time series (Makridakis, 1983).

One of the methods used for forecasting is the Autoregressive Integrated Moving Average (ARIMA) method. ARIMA was developed by George E. P. Box and Gwilym M. Jenkins in 1970 for time series analysis and forecasting (Cryer & Chan, 2008). This method is reliable for short-term forecasting; however, its accuracy tends to decline when applied to long-term forecasting (Brockwell & Davis, 1996). For forecasting SOI data, it is expected that the predictions can be made over the long term.

In this case, a machine learning approach can be used, as machine learning develops models that can learn from data and make predictions or decisions without being explicitly programmed for specific tasks. One such machine learning approach is the Artificial Neural Network (ANN). Unlike ARIMA, ANN models do not require assumptions (Kusumadewi, 2014).

Artificial Neural Networks (ANN) are a forecasting method that can be used to predict nonlinear time series (Hikmah, 2017). According to Fausett (1994), ANN has become an important research subject in the fields of artificial intelligence and cognitive computing. ANN is capable of modeling and solving various problems, such as pattern recognition, prediction, and nonlinear data processing.

2. METHODS

Data

The data used in this study are secondary data. The data were obtained from the official website of the Australian Government Bureau of Meteorology (www.bom.gov.au). The dataset consists of monthly SOI data from January 2004 to December 2023, with a total of 240 observations.

Research Method

Artificial Neural Network

Artificial Neural Network (ANN) is an information processing system that resembles biological neural networks. ANN is an artificial representation of the human brain, designed to simulate the learning processes of the human brain (Fausett, 1994). *Artificial Neural Network* consists of interconnected neurons. The neurons are linked by weights, which transmit signals from one neuron to another. Each neuron can receive multiple inputs and generate a single output.

Artificial Neural Network Architecture

In general, the architecture of an Artificial Neural Network (ANN) can be observed from the number of layers and the number of neurons in each layer. The ANN consists of three layers: the input layer, hidden layer, and output layer (Pradana et al., 2022).

Weight Initialization

Weights represent the information used by the network to solve problems. Weight initialization is performed randomly. Random initialization is the most used method for initializing weights (Kholis & Rofii, 2017). According to Fausett (1994), weight initialization is done with small random numbers. Initial weight initialization is carried out before the training process begins and is applied to each neuron that is interconnected.

Binary Sigmoid Activation Function

The activation function is used to update the weight values based on all input values. In backpropagation, the activation function is crucial, as it determines the magnitude of the weights (Puspitaningrum, 2006). Activation function in ANN, when the output values need to be in the range from 0 to 1, the binary sigmoid function is commonly used because it produces values within the range (0, 1). The binary sigmoid function is defined as follows (Fausett, 1994).

$$f(x) = \frac{1}{1+e^{-x}} \quad (1)$$

where $f(x)$ is the binary sigmoid activation function, and e^{-x} is the exponential value.

Data Normalization

Normalization is the process applied to raw data to ensure that the data used falls within a specific range (Budianita & Prijodiprodjo, 2013). The goal of the normalization process is to transform the data so that its range is not too wide, while still preserving the original characteristics of the data. Normalization is necessary because the activation function used is the binary sigmoid function, which is an asymptotic function that never reaches 0 or 1. Therefore, data normalization is performed by transforming the data into a smaller interval using the following formula (Siang, 2005):

$$X' = \frac{0,8(x - a)}{b - a} + 0,1 \quad (2)$$

where X' is the normalized data, x is the original data, a is the minimum value, and b is the maximum value.

Backpropagation

Backpropagation was popularized by Rumelhart, Hinton, and Williams in 1986 for use in neural networks (Kusumadewi, 2004). Backpropagation is one of the most used ANN algorithms to solve problems related to identification, prediction, pattern recognition, and others (Anwar, 2011). Backpropagation uses a weight adjustment pattern to minimize the error between the forecasted output and the actual output (Junaidi et al., 2022). Backpropagation is a procedure that iteratively adjusts the connection weights in the network to minimize the discrepancy between the actual network output and the desired output (Rumelhart, Hinton, & Williams, 1986). The backpropagation training algorithm, according to Fausett (1994), is as follows:

Phase I : Feedforward Propagation

The first step is to initialize the weights and biases with small random numbers. Then, each input value ($x_i, i = 1, \dots, n$) receives a signal and passes this signal to all units in the hidden layer. The hidden layer units ($z_j, j = 1, \dots, p$) compute the weighted sum of the input signals,

$$z\_in_j = v_{0j} + \sum_{i=1}^n x_i v_{ij} \quad (3)$$

Next, the activation function is applied to compute the output signal,

$$z_j = f(z\_in_j) \quad (4)$$

where z_in_j is the z input to the j -th hidden unit, v_{0j} is the bias weight for the j -th hidden layer, x_i is the input value from the i -th unit in the input layer, v_{ij} is the weight from the i -th unit in the input layer to the j -th unit in the hidden layer, and z_j is the output of the j -th hidden unit.

For the output layer, the process is similar. Each output unit ($y_k, k = 1, \dots, m$) computes the weighted sum of the input signals,

$$y\_in_k = w_{0k} + \sum_{j=1}^p z_j w_{jk} \quad (5)$$

Then, the activation function is applied to compute the output signal,

$$y_k = f(y\_in_k) \quad (6)$$

where y_in_k is the k -th input observation for the output layer, w_{0k} is the bias weight for the k -th unit in the hidden layer, z_j is the j -th unit in the hidden layer. w_{jk} is the weight from the j -th unit in the hidden layer to the k -th unit in the output layer, and y_k is the k -th output observation in the output layer.

Next, the error is calculated using the Mean Squared Error (MSE) function before backpropagation,

$$MSE = \frac{1}{n} \sum_{t=1}^n (t_k - y_k)^2 \quad (7)$$

where n is the number of data points, t_k is the target output for the k -th unit, and y_k is the output from k -th unit in the output layer

Phase II : Backpropagation

Each output neuron ($y_k, k = 1, \dots, m$) receives the target pattern corresponding to the input pattern during training. Then, the error correction factor for each layer is computed,

$$\delta_k = (t_k - y_k)y_k(1 - y_k) \quad (8)$$

where δ_k is the error correction factor for the weight w_{jk} .

The weight correction is computed for later use to adjust w_{jk} ,

$$\Delta w_{jk} = \alpha \delta_k z_j \quad (9)$$

The bias correction for later use to adjust w_{0k} is calculated as,

$$\Delta w_{0k} = \alpha \delta_k \quad (10)$$

where Δw_{0k} is the bias correction for the k -th output layer, Δw_{jk} is the weight correction from the j -th unit in the hidden layer to the k -th unit in the output layer, α is the learning rate, and δ_k is the error correction factor for the weight w_{jk} .

Each hidden unit ($z_j, j = 1, \dots, p$) computes the sum of the inputs from the above layer (output layer),

$$\delta_{in_j} = \sum_{i=1}^m \delta_k w_{jk} \quad (11)$$

Then, the derivative of the activation function is applied to compute the error correction factor,

$$\delta_j = \delta_{in_j} z_j(1 - z_j) \quad (12)$$

where δ_{in_j} is the δ input to the j -th hidden unit, δ_k is the error correction factor for the weight w_{jk} , w_{jk} is the weight from the j -th unit in the hidden layer to the k -th unit in the output layer, is the error correction factor for the weight v_{ij} .

The weight correction for v_{ij} is computed as,

$$\Delta v_{ij} = \alpha \delta_j x_i \quad (13)$$

The bias correction for v_{0j} is calculated as,

$$\Delta v_{0j} = \alpha \delta_j \quad (14)$$

where Δv_{ij} is the weight correction for v_{ij} , Δv_{0j} is the bias correction for v_{0j} , α is the learning rate constant, δ_j is the error correction factor for the weight v_{ij} , x_i is the input value in the j -th unit of the input layer.

Phase III : Weight and Bias Update

Each output unit ($y_k, k = 1, \dots, m$) and each hidden unit ($z_j, j = 1, \dots, p$) computes the weight update,

$$w_{jk}(\text{new}) = w_{jk}(\text{old}) + \Delta w_{jk} \quad (15)$$

$$v_{ij}(\text{new}) = v_{ij}(\text{old}) + \Delta v_{ij} \quad (16)$$

Each output unit ($y_k, k = 1, \dots, m$) and hidden unit ($z_j, j = 1, \dots, p$) computes the bias update,

$$w_{0k}(\text{new}) = w_{0k}(\text{old}) + \Delta w_{0k} \quad (17)$$

$$v_{0j}(\text{new}) = v_{0j}(\text{old}) + \Delta v_{0j} \quad (18)$$

Finally, the stopping condition is checked when the target error is achieved. If the stopping condition is met, the network training is stopped. Otherwise, the forward propagation steps are repeated until the weight and bias changes reach the stopping condition.

Data Denormalization

Denormalization is the process of converting normalized values back to their original scale, where the initial data was within the range [0, 1]. The data is then transformed into its original or pre-normalization values using the following formula (Siang, 2005):

$$x = \left[\frac{(X' - 0,1)}{0,8} \right] + (b - a) + a \quad (19)$$

where X' is the predicted value from the normalized data, x is the predicted value with the original range, a is the minimum data value, and b is the maximum data value.

Mean Squared Error

According to Suryaningrum (2015), *Mean Squared Error* (MSE) is another method for evaluating forecasting methods. Each error or residual is squared. MSE is the average squared difference between the forecasted values and the observed values. The formula for calculating MSE is as follows:

$$MSE = \frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2 \quad (20)$$

where n is the number of data points, y_t is the actual value for period- t , $\hat{y}_t$ is the forecasted value for period- t .

Forecasting Accuracy

Forecasting accuracy can be calculated by determining the error rate. One method for calculating forecasting error is the Mean Absolute Percentage Error (MAPE). MAPE is calculated by measuring the percentage difference between the forecasted values and the actual data. The formula for calculating MAPE is as follows:

$$MAPE = \frac{100\%}{n} \sum_{t=1}^n \left| \frac{y_t - \hat{y}_t}{y_t} \right| \quad (21)$$

where n is the number of data points, $\hat{y}_t$ is the forecasted value for period- t , and y_t is the actual value for period- t . The MAPE criteria are as shown in Table 1 (Lewis, 1982).

Table 1. The MAPE Criteria

MAPE	Forecasting Ability
< 10%	Excellent
10% - 20%	Good
20% - 50%	Fair
> 50%	Poor

3. RESULTS

Descriptive Analysis

As shown in Figure 1, the SOI index is not always stable. The highest SOI value reached 27,1 in December 2010, indicating the occurrence of the La Niña phenomenon, which can cause increased rainfall intensity in Indonesia. The lowest SOI value of -28,6 occurred in February 2005, indicating the opposite phenomenon, El Niño, which can lead to a decrease in rainfall intensity in Indonesia. The average SOI index during the period from 2004 to 2023 is 1,36, with a standard deviation of 10,37.

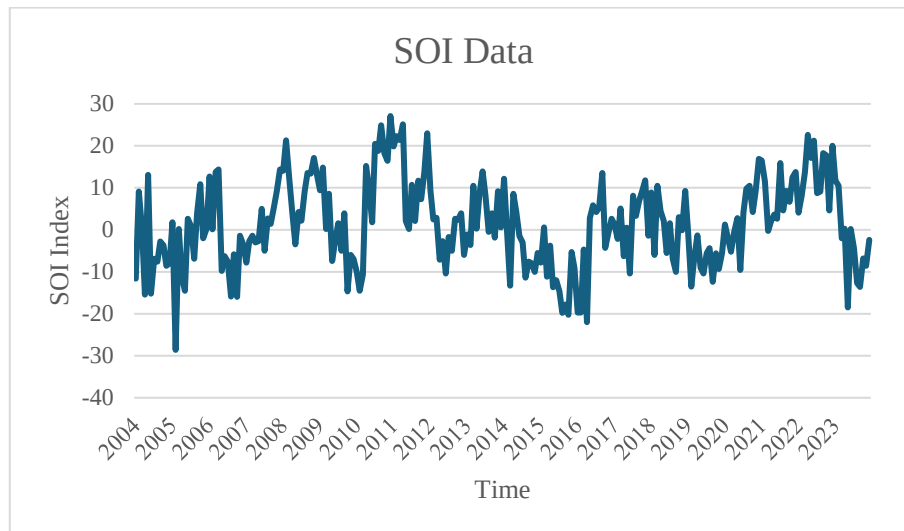


Figure 1. SOI Index Graph

ANN Model Architecture

Table 2 presents the ANN model architectures used.

Table 2. The list of ANN model architectures to be developed

Architecture
12 – 5 – 1
12 – 6 – 1
12 – 7 – 1
12 – 8 – 1
12 – 9 – 1
12 – 10 – 1

Training Model of ANN

Table 3 shows the results of each architecture that achieved the target error at the last epoch. The next step involved forecasting using the training data for each architecture to select the best one based on MSE and MAPE values.

Table 3. MSE Results of Each Architecture in the Final Epoch of Training Data

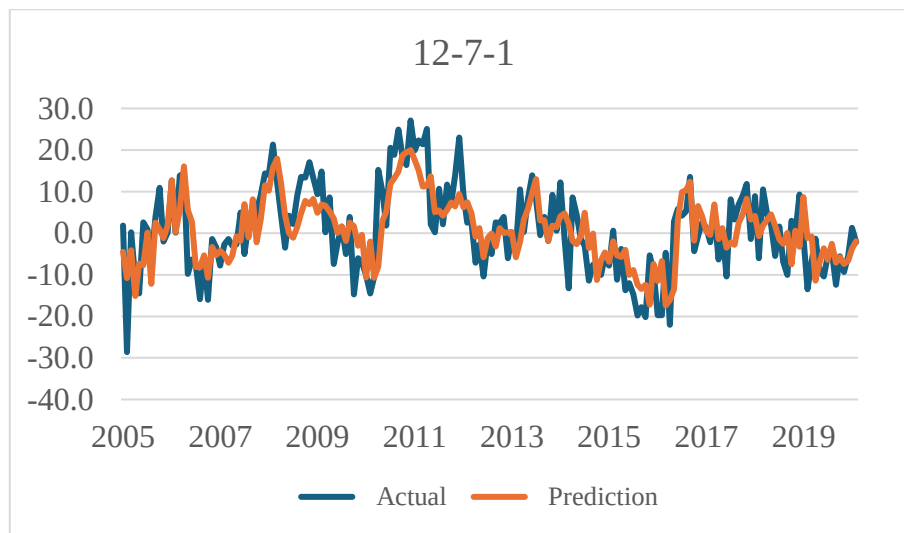
Architecture	MSE	Epoch
12-5-1	0,0078	315
12-6-1	0,0087	306
12-7-1	0,0094	716
12-8-1	0,0083	348
12-9-1	0,0091	310
12-10-1	0,0098	644

As shown in Table 4, the lowest MSE and MAPE values from the training data forecast were achieved by the 12-7-1 architecture, with an MSE of 0.0095 and a MAPE of 17.6851. Therefore, the 12-7-1 architecture was identified as the best model.

Table 4. MSE and MAPE Results from Forecasting the Training Data

Architecture	MSE	MAPE
12-5-1	0,0109	19,2809
12-6-1	0,0103	18,4122
12-7-1	0,0095	17,6851
12-8-1	0,0111	19,4064
12-9-1	0,0109	19,2333
12-10-1	0,0128	18,2269

Figure 2 shows the results of forecasting the training data for the 12-7-1 architecture.

**Figure 2. Forecasting Results for Training Data of the 12-7-1 Architecture**

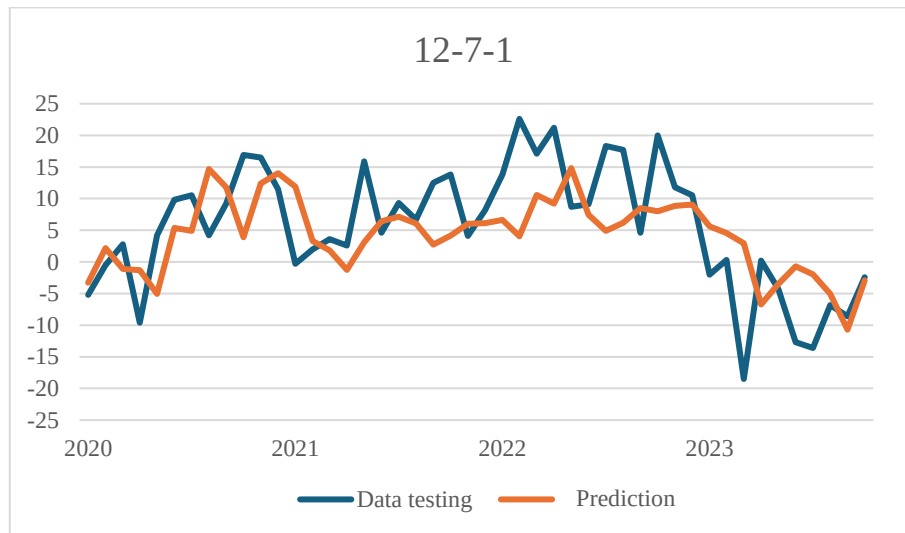
Forecasting for Testing Data

Table 5. presents the MSE and MAPE values achieved by 12-7-1 architecture model, with a MSE of 0,0136 and a MAPE of 17,3304. It can be seen that the MAPE value from the developed model is below 20%, indicating that the model has good forecasting capability.

Table 5. MSE and MAPE Results for Forecasting the Testing Data of the 12-7-1 Architecture

Architecture	MSE	MAPE
12-7-1	0,0136	17,3304

Figure 3. shows the results of forecasting with the 12-7-1 architecture on testing data, where the model is still unable to accurately capture the actual pattern.

**Figure 3. Forecasting Results of the 12-7-1 Architecture ANN Model for Testing Data**

Based on the calculations performed, the results can be interpreted into the following formula:

$$z_j = f(v_{0j} + \sum_{i=1}^n x_i v_{ij}) \quad (22)$$

$$z_1 = f((-0,8070) + x_1 * (-0,6400) + x_2 * (3,3997) + x_3 * (-1,4594) + x_4 * (-0,2872) + x_5 * (-3,9883) + x_6 * (0,0507) + x_7 * (-6,7996) + x_8 * (4,2079) + x_9 * (-1,5605) + x_{10} * (-0,8725) + x_{11} * (0,1745) + x_{12} * (2,7903))$$

$$\cdot$$

$$\cdot$$

$$\cdot$$

$$z_7 = f((-0,1811) + x_1 * (3,0954) + x_2 * (9,4052) + x_3 * (7,4076) + x_4 * (-3,3386) + x_5 * (0,6367) + x_6 * (2,8014) + x_7 * (-0,7642) + x_8 * (7,3212) + x_9 * (0,2957) + x_{10} * (-6,5738) + x_{11} * (-1,8439) + x_{12} * (-11,4480))$$

z_j represent the *output* in the *hidden layer* after being activated using the binary sigmoid activation function. Then v_{0j} is the weight between the input layer and the hidden layer. The mathematical model of the ANN obtained by applying the activation function is as follows:

$$y_k = f(w_{0k} + \sum_{j=1}^p z_j w_{jk}) \quad (23)$$

$$y_k = f((0,3940) + z_1 * (-0,9091) + z_2 * (-1,4965) + z_3 * (1,8943) + z_4 * (-0,9112) + z_5 * (-1,7816) + z_6 * (-1,3158) + z_7 * (-0,9794))$$

y_k is the output of the forecasted SOI index value for the k -th instance after being activated using the binary sigmoid activation function. Meanwhile, w_{ok} is the bias, and w_{jk} is the weight between the *hidden layer* and the *output layer*, serving as an additional parameter that can take both positive and negative values, allowing it to adjust the *output* of the SOI index forecast.

Future Forecasting

Figure 4. shows the forecast for the next 12 months using the 12-7-1 architecture. The SOI index is expected to move from negative values at the start of the year to more positive values towards the end of the year.

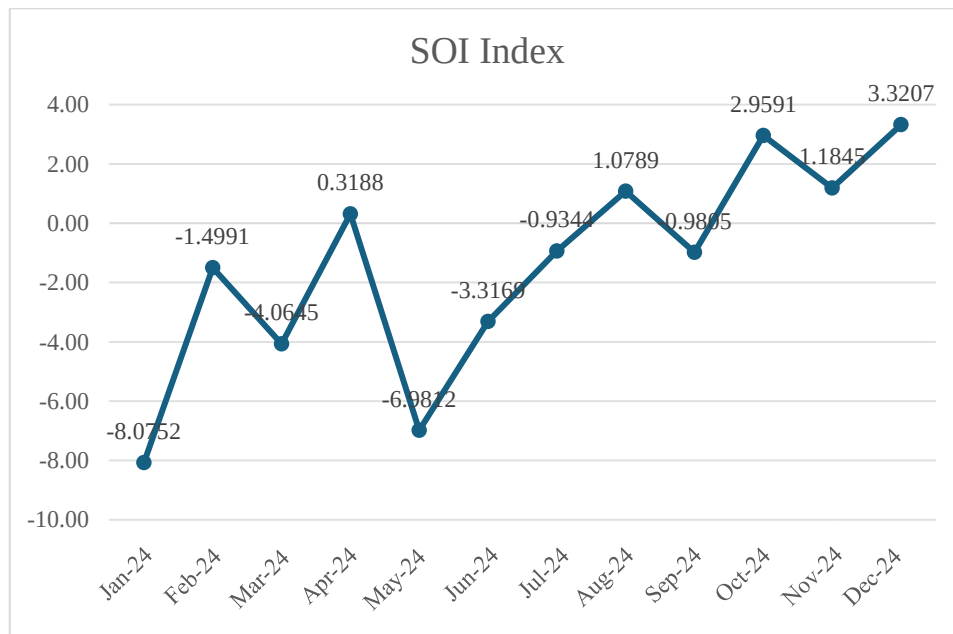


Figure 4. Forecasting Results for the Next 12 Months

4. DISCUSSIONS

The Southern Oscillation Index (SOI) exhibits significant fluctuations, making it inherently challenging to predict with high precision. Historically, these fluctuations have provided crucial insights into atmospheric and oceanic interactions, particularly in understanding phenomena such as El Niño and La Niña events, which significantly influence global weather patterns. Before the forecasted period, the SOI index demonstrated a cyclical pattern, with notable variations corresponding to major climatic events. These patterns have had profound implications on agricultural yields, water resource management, and disaster preparedness in regions highly sensitive to climate variability. For the post-forecast period, the predicted values indicate potential trends that could offer early warning signals for policymakers and practitioners in weather-related fields.

The results from this study, which applied an Artificial Neural Network (ANN) model to forecast the SOI, demonstrate a promising predictive capability. Specifically, the 12-7-1 ANN architecture achieved the lowest Mean Squared Error (MSE) of 0.0095 and Mean Absolute Percentage Error (MAPE) of 17.6851, indicating that the model can effectively capture the inherent variability of the SOI. This finding is consistent with the general benchmark for good forecasting performance in time series prediction, where MAPE values below 20% are considered acceptable. This level of precision

is significant, as it provides accurate early warning signals, which could prove invaluable for policymakers in regions sensitive to climate variability.

To contextualize the findings of this research, it is crucial to compare them with those from prior studies. One key study by Baawain et al. (2005) used a combination of SOI and Niño3 indices to predict ENSO events and found that their model was successful in forecasting with 75% accuracy. In this study, their approach involved comparing the predictions of the two ENSO indicators, finding good agreement between them, which validated their method. While the accuracy reported in Baawain et al. is commendable, the current study shows a slightly better predictive performance, as evidenced by lower MSE and MAPE values. The 12-7-1 ANN architecture appears to be more suited for capturing the cyclical nature of SOI, leading to a more refined and precise forecast.

Furthermore, Aprilia et al. (2021) applied an ANN-backpropagation method to predict ENSO using several indices, including the Nino 3.4 index. Their findings for the 2020/2021 period indicated normal climatic conditions (no significant El Niño or La Niña events), with their model showing high accuracy when compared to the International Research Institute (IRI) model. While their results were accurate in predicting normal conditions, our study's results, with more granular MAPE figures below 20%, suggest that the ANN model employed here has a higher degree of precision in predicting the SOI itself, which is a critical precursor to ENSO events.

Additionally, Yan et al. (2020) introduced a hybrid model that combines Ensemble Empirical Mode Decomposition (EEMD) and Temporal Convolutional Networks (TCN) to predict ENSO events, including SOI. Their study demonstrated that the EEMD-TCN model outperformed traditional methods, with a notably high prediction accuracy for the one-month lead (RMSE = 0.2337 and PCC = 0.9658) and decreasing accuracy as the prediction horizon extended to 12 months (RMSE = 0.5142, PCC = 0.8297). However, the model's accuracy for SOI predictions was lower compared to that for the Niño 3.4 index, likely due to the high-frequency components present in SOI data, which pose difficulties for prediction. In comparison, our study shows promising results for SOI forecasting with the ANN model, yielding lower MAPE values (below 20%) and better overall prediction performance, particularly when forecasting the SOI directly. This suggests that while the hybrid EEMD-TCN model excels in some aspects, the ANN model we applied might be more effective in capturing SOI's cyclical nature and providing timely, precise predictions.

Moreover, Ouyang et al. (2017) applied Support Vector Machines (SVM) to predict ENSO events, achieving promising results with an accuracy rate of 81.3%. While their model showed good performance for ENSO prediction, it did not outperform the ANN-based models in this study. Our ANN model, with lower MSE and MAPE values, seems to capture the nonlinear relationships in SOI fluctuations more effectively, providing more precise predictions. This highlights the flexibility and precision of ANN models when compared to more traditional machine learning approaches like SVM for time series prediction.

Additionally, Lee et al. (2018) proposed a hybrid approach combining Artificial Neural Networks (ANN) with an ensemble of other techniques to predict ENSO events. Their study highlighted the importance of integrating multiple models to enhance prediction accuracy, especially in complex phenomena like ENSO. While their hybrid ANN model showed significant improvements over standalone models, the ANN architecture used in this study still provides strong performance with lower MAPE values, suggesting that a well-optimized ANN can perform on par with hybrid approaches in certain cases.

The findings from these studies show the utility of ANN models and hybrid approaches in forecasting climate phenomena, but our study's performance, particularly in terms of forecasting the SOI index with lower errors, suggests that the architecture used in this study may be more effective in capturing the dynamics of SOI fluctuations.

The implications of this research are far-reaching. By providing accurate forecasts of the SOI, this study contributes to the broader field of climate prediction, particularly for regions that are highly vulnerable to the impacts of ENSO events. The predictive accuracy of the ANN model used here could serve as a vital tool for policymakers in weather-dependent sectors such as agriculture, water management, and disaster preparedness. The ability to forecast SOI dynamics with high precision would enable early warnings, thus providing stakeholders with the time necessary to implement mitigation strategies for adverse climatic events.

Furthermore, the integration of SOI predictions into long-term planning can enhance the resilience of socio-economic sectors that rely heavily on predictable seasonal weather patterns. For example, the agricultural sector, which is often at the mercy of El Niño and La Niña phenomena, could benefit greatly from accurate SOI forecasts, allowing farmers to prepare for potential disruptions in rainfall patterns and temperatures. This would also help optimize water resource management and improve disaster response strategies.

5. CONCLUSION

Based on the forecasting for the training data, the model with the 12-7-1 architecture is the best, as it achieved the lowest MSE and MAPE values, with an MSE of 0.0095 and a MAPE of 17.6851. Meanwhile, the highest MSE and MAPE values were achieved by the 12-5-1 architecture model, with an MSE of 0.0109 and a MAPE of 19.2809.

Based on the forecasting for the training data, the MAPE values from the models developed were all below 20%, indicating that the models have good forecasting capabilities.

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