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APPLICATION OF BACKPROPAGATION FOR FORECASTING OPEN UNEMPLOYMENT IN MAKASSAR CITY

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ABSTRACT

Based on data from the Statistics Bureau of South Sulawesi Province, the open unemployment rate in Makassar City has remained consistently high over the past ten years, averaging 11.41%. This highlights a persistent labor market issue and positions Makassar as the leading contributor to the open unemployment rate in the province. To support effective policymaking and early intervention strategies, it is essential to forecast future unemployment trends based on historical data. Therefore, this study aims to forecast the open unemployment rate in Makassar City over the next five years using a machine learning approach. Among the available forecasting methods, the Backpropagation Artificial Neural Network (ANN) was selected due to its proven ability to model complex, non-linear relationships often found in socio-economic data. ANN is particularly effective in handling temporal dynamics without assuming linearity or stationarity, unlike traditional statistical models. In this study, the forecasting process involved data normalization, scenario-based data partitioning, ANN architecture design, and model training and testing. The model with the best performance consisted of 11 neurons in the input layer, 55 neurons in the hidden layer, and 1 neuron in the output layer, using 80% of the data for training and 20% for testing. This configuration yielded a forecasting accuracy of 91.896%, with a MAPE of 8.131% and an MSE of 0.003. The denormalized results forecast a steady decline in the open unemployment rate from 9.078% in 2023 to 7.248% in 2027, indicating a positive trend in employment. Nevertheless, it is important to acknowledge the limitations of forecasting models and the potential influence of external factors that may affect actual outcomes.

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1. INTRODUCTION

Unemployment, along with poverty, remains a significant issue that Indonesian society faces year after year. Currently, unemployment is a major concern that requires immediate attention. One of the primary causes of rising unemployment in Indonesia is the lack of effort by both the government and the private sector to create jobs. Additionally, low education levels and a lack of adequate human resources make it difficult for people to find employment [1]. Unemployment can be categorized into three types based on working hours: disguised unemployment, underemployment, and open unemployment [2]. The focus of this study is on open unemployment, which includes individuals who do not have a job and are actively seeking one, individuals who do not have a job and are preparing to start a business, and individuals who do not have a job and are not actively seeking one because they believe it is difficult to find employment. Open unemployment may also include individuals who have a job but have not yet started working [3]. The International Labor Organization (ILO) describes unemployment, or open unemployment, as a condition where an individual of working age has not been employed for a specific period, is actively seeking work, and is willing to accept employment. Economists analyze unemployment to understand its root causes and to improve public policies that influence employment levels [4].

According to data from the Central Statistics Agency [5], the open unemployment rate in South Sulawesi in 2019 reached 4.62% and experienced a rapid increase in 2020 with a percentage of 6.31%. Makassar City, as one of the cities in South Sulawesi, is the largest contributor to open unemployment in South Sulawesi, with a percentage of 9.83% of the total Open Unemployment Rate (TPT) in South Sulawesi and 15.92% in 2020. The open unemployment rate in Makassar City over the past 10 years has been very high, with an average open unemployment rate of 11.41% over the past 10 years, indicating a serious problem in terms of the unemployment rate in Makassar City. Information on the unemployment rate from time to time is very important for the government because it helps in making policies to address and control the unemployment problem. Various methods have been developed to forecast the unemployment rate or similar problems [6].

Forecasting can be conducted using various models, including the Artificial Neural Network (ANN). ANNs are computational models inspired by the workings of the human nervous system, consisting of interconnected processing units called neurons. One of the most widely used architectures is the Multi-Layer Perceptron (MLP), which follows a feed-forward structure and is commonly trained using the Backpropagation algorithm [7]. This method minimizes the error between the predicted output and the actual output through iterative adjustments [8]. An artificial neural network is a data model that can effectively represent and capture complex input-output relationships. Its ability to easily solve various problems, speed in processing data, and ability to overcome the complexity of system initialization make it an efficient and powerful solution for modeling [9]. Artificial neural network (ANN) models especially in a multivariate setting have been shown to outperform traditional models such as ARIMA and SVM in forecasting unemployment rates, demonstrating high levels of prediction accuracy as well as good adaptability. Therefore, ANN was chosen in this study due to its proven effectiveness in capturing complex patterns in unemployment trends [10].

The practical concept of artificial neural networks for forecasting the number of unemployed is based on the pattern of unemployment data from previous periods that is input into the system. The system is then trained using an artificial neural network and a training algorithm using Backpropagation. After the training process is complete, the system will generate weights that will be used to forecast the number of unemployed for future years [11].

Several studies have been conducted on the use of Backpropagation neural networks. The research conducted by [11], this study investigated the implementation of artificial neural networks to forecast the number of unemployed individuals in East Kalimantan Province. The proposed model achieved an impressive forecasting accuracy rate of 95.18%. Another research by [2], their research focused on applying Backpropagation neural networks to forecast the Open Unemployment Rate (TPT) in Maluku Province. The analysis of training data using the Backpropagation method yielded an average forecasting success rate of 82.2%.

This study aims to provide information on open unemployment forecasting for the next 5 years in Makassar City, which can be used as a consideration for the Makassar City government in making policies to address unemployment. It also serves as a means of developing insights for the reader.

2. RESEARCH METHODS

2.1 Artificial Neural Network

Artificial neural networks (ANNs) are a computational model inspired by the structure and functions of the human brain. They aim to replicate the brain's learning process and ability to handle complex information [11]. ANNs are designed to model the parallel processing capabilities of the human brain, enabling efficient computation and problem-solving [12]. ANNs operate by learning from provided training examples. During this learning process, both input data and corresponding output values are presented simultaneously [7]. The network consists of interconnected nodes, analogous to neurons in the biological brain, with weighted connections representing the strengths of the signals transmitted between neurons, with the assumption that:

1. Information Processing by Simple Elements (Neurons)
2. Signal Transmission Through Connections
3. Connections between neurons are assigned weights, representing the relative importance of each connection in influencing the overall output.
4. Neuron applies an activation function to its weighted inputs, determining whether to fire and transmit a signal. This function introduces non-linearity into the network, enabling it to learn complex relationships.

2.2 Fundamental Concepts of Artificial Neural Networks

Artificial neural networks (ANNs) operate on the fundamental principle that each pattern of input and output information is processed within neurons. These neurons are organized into layers, referred to as neuron layers [13]. The layers in an ANN can be broadly classified into three categories [14].

1. The input layer consists of units that receive input data patterns from the external environment, representing the problem at hand.
2. The hidden layer comprises units that process input data and generate outputs that are not directly observable. These units play a crucial role in extracting hidden features and patterns from the input data.
3. The output layer consists of units that produce the final solution or output of the ANN, representing the network's response to the given problem.

2.3 Artificial Neural Network Architectures

Artificial neural networks (ANNs) have several architectures that are commonly used in various situations [15]. Artificial Neural Network architectures as illustrated at Figure 1-3.

1. Single Layer Network

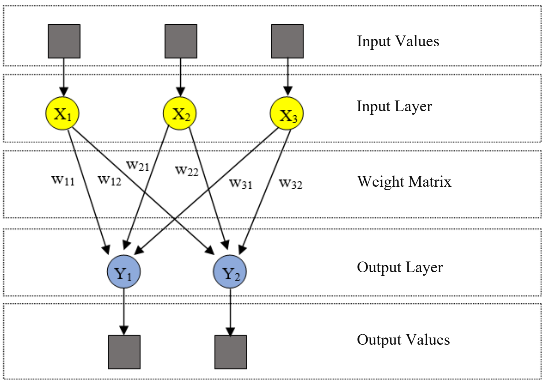

Figure 1. Single Layer Network Architecture [7]

Figure 1 shows a single layer network consists of 1 input layer and 1 output layer. Each neuron in the input layer is always connected to each neuron in the output layer. This network only receives input and then directly processes it into output without having to go through the hidden layer.

2. Multilayer Network

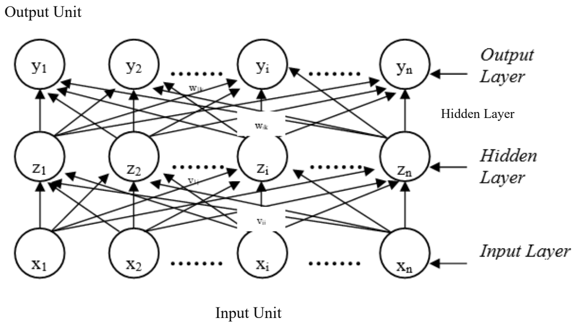

Figure 2. Multilayer Network Architecture [7]

A multi-layer network has certain characteristics, namely it has 3 types of layers, namely the input layer, the output layer, and the hidden layer as in **Figure 2**. This multi-layer network can solve more complex problems than a single-layer network. However, the training process often takes a long time.

3. Competitive Layer

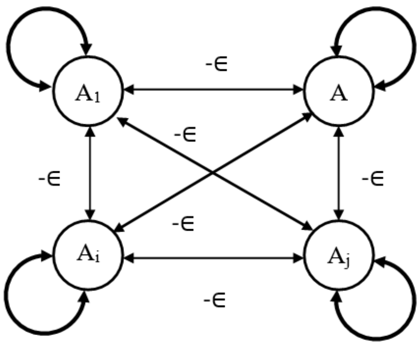

Figure 3. Competitive Layer Architecture [7]

Figure 3 shows a group of neurons compete with each other to become the sole active unit through a "winner-takes-all" mechanism. This competition is based on actors like weight strength or activation level, allowing only the winning neuron to adjust its weights according to the input pattern.

2.4 Structure of Artificial Neural Networks

Artificial neural networks (ANNs) exhibit adaptive learning capabilities, enabling them to learn from past data and recognize evolving patterns **[16]**. Similar to the human brain, ANNs comprise interconnected neurons, as illustrated in **Figure 4 [9]**.

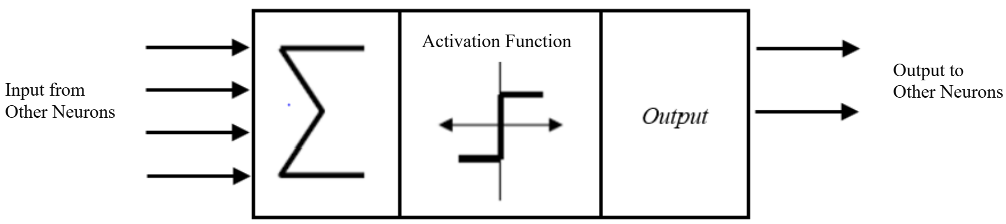

Figure 4. Structure of an ANN Neuron [9]

Artificial neurons employed in ANNs are typically non-linear, producing continuous outputs and performing simple functions. These functions include gathering available input signals, assembling them according to their operational function, and generating a response based on their inherent activation function.

The simplest neuron model, encompassing the key biological features of parallel processing and high connectivity, was proposed by McCulloch and Pitts in 1943. This model remains widely used in various ANN architectures. According to [17], an ANN consists of seven fundamental elements:

1. Input Signal $(x_1, x_2, \dots, x_n)$
2. Synaptic Weight $(w_1, w_2, \dots, w_n)$
3. Linear Aggregator (Σ)
4. Activation treshold or bias (θ)
5. Activation Potential (u)
6. Activation Function (g)
7. Output Signal (y)

2.5 Activation Functions in Backpropagation

Activation functions are mathematical functions employed in neural networks to determine whether a neuron should be activated or not. For backpropagation neural networks, activation functions should exhibit the following characteristics: continuity, differentiability, and non-monotonic decreasing behavior [18].

1. Binary Sigmoid Function

   The binary sigmoid function depends on a steepness parameter (σ). To ensure that the function outputs values within the binary range (0 to 1), σ is set to 1, resulting in a continuous non-linear graph [19]. The Function is represented by Equation (1) and illustrated in Figure 5.

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

   The derivative of the binary sigmoid function is expressed in Equation (2)

$$f'(x) = \sigma f(x)[1 - f(x)] \tag{2}$$

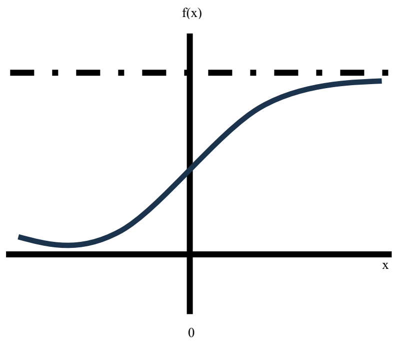

Figure 5. Binary Sigmoid Function

2. Bipolar Sigmoid Function

   Similar to the binary sigmoid function, the bipolar sigmoid function also depends on a steepness parameter (σ). However, the bipolar sigmoid function extends the binary sigmoid function to include negative values across the x-axis [19]. The bipolar sigmoid function has a value range of [-1,1], as represented by Equation (3) and illustrated in Figure 6.

$$f(x) = 2\, f(x) - 1 = \frac{2}{1 + e^{-\sigma x}} - 1 = \frac{1 - e^{-\sigma x}}{1 + e^{-\sigma x}} \tag{3}$$

   The derivative of the bipolar sigmoid function is expressed in Equation (4)

$$f'(x) = \frac{\sigma}{2}[1 + f(x)][1 - f(x)] \tag{4}$$

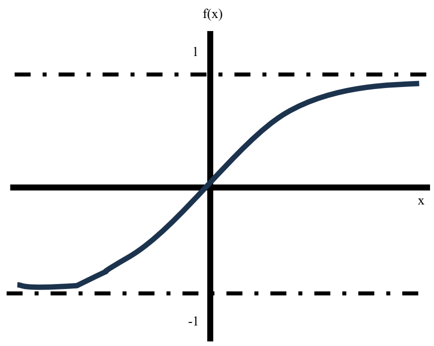

Figure 6. **Bipolar Sigmoid Function**

2.6 Backpropagation Learning Algorithm

The Backpropagation algorithm is a widely used supervised learning method for training artificial neural networks. It involves a two-phase process: feedforward and backpropagation.

1. Feedforward

   The feedforward phase involves propagating information forward through the network, from the input layer to the output layer [20]. This phase can be summarized in the following steps [21].

   Step 0. Initialize all weights with small random values;

   Step 1. As long as the stopping condition is not met (Epoch < Maximum Epoch): Increment the epoch counter Epoch = Epoch + 1, and perform steps 2-9.

   Step 2. For each training data point, perform steps 3-8.

   Step 3. Each input unit (x_i, $i = 1, 2, \ldots, n$) receives the input signal and forwards it to all units in the hidden layer.

   Step 4. Each hidden unit (z_j, $j = 1, 2, \ldots, p$); calculates the weighted sum of its inputs, including the bias, as shown in **Equation (5)**.

$$z_{in_j} = v_{b_j} + \sum_{i=1}^{n} x_i . v_{i_j} \tag{5}$$

   Then, calculate the output signal of the hidden unit using the chosen activation function, typically the binary sigmoid function, as shown in **Equation (6)**.

$$z_j = f\left(z_{in_j}\right) = \frac{1}{1 + e^{-z_{in_j}}} \tag{6}$$

   This output signal is then forwarded to all units in the output layer.

   Step 5. Each output unit (y_k, $k = 1, \ldots, m$); calculates the weighted sum of its inputs as shown in **Equation (7)**.

$$y_{in_k} = v_{b_k} + \sum_{j=1}^{p} z_j . w_{j_k} \tag{7}$$

   This output signal is then passed to all output units to initiate the backward phase.

2. Backward

   The backward phase in the Backpropagation algorithm involves propagating error signals backward through the network, updating the weights and biases of each neuron to minimize the overall error [20]. This phase follows the feedforward phase and plays a crucial role in training the network [21].

Step 6. Each output unit (y_k, k = 1,..., m); receives a corresponding target pattern from the training input pattern, **Equation (7)** used to Calculate the error (δ_k) between the target and the network's output using **Equation (8)**.

$$\delta_k = (t_k - y_y)f'(y_{in_k}) = (t_k - y_y)y_k(1 - y_k) \tag{8}$$

Calculate the error correction factor (Δw_{j_k}) which will be used for weight adjustment as shown in **Equation (9)**.

$$\Delta w_{j_k} = a\delta_k z_j \tag{9}$$

Calculate the bias correction (Δw_{0k}) using **Equation (9)**. which will be used for bias adjustmentas shown in **Equation (10)**.

$$\Delta w_{0_k} = a\delta_k \tag{10}$$

The error correction factor (δ_k), which represents the unit error, is then passed to the weight update step 7.

Step 7. Each hidden unit $z_j, j = (1,2, \dots, p)$; receives a weighted input (from step 6) as shown in **Equation (11)**.

$$\delta_{in_j} = \sum_{k=1}^{m} \delta_k . w_{j_k} \tag{11}$$

Multiply the result of **Equation (11)** by the derivative of the activation function used in the hidden layer to calculate the error information δ_i as shown in **Equation (12)**.

$$\delta_j = \delta_{in_j} f'\left(z_{in_j}\right) = \delta_{in_j} z_j(1 - z_j) \tag{12}$$

Calculate the weight update term Δv_{ij} using **Equation (13)**.

$$\Delta v_{i_j} = a\delta_j x_i \tag{13}$$

Calculate the bias correction using **Equation (14)**.

$$\Delta w = a\delta_j \tag{14}$$

The weights and biases of the hidden layer are updated.

Step 8. Each output unit ($Y_k, k = 1,2, \dots, m$); updates the weights and biases of each hidden unit ($j = 0,1, \dots, p$) using Equations **Equation (15)** and **Equation (16)**.

$$w_{j_k}(new) = w_{j_k}(old) + \Delta w_{j_k} \tag{15}$$

and

$$b_{0_k}(new) = b_{0_k}(old) + \Delta b_{0_k} \tag{16}$$

Step 9. Check the stopping condition if the error is sufficiently small and the epoch has reached the maximum allowed number. If the stopping condition is met, terminate the network training.

2.7 Error Calculation

Error calculation is a crucial aspect of neural network training, as it measures the network's accuracy in recognizing the given patterns. Several error calculation methods are commonly used, including Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE) [22].

MSE is a widely used error metric for evaluating the performance of neural networks. It measures the average squared difference between the predicted values (network outputs) and the actual target values. A lower MSE value indicates a better fit of the network to the training data. Checking the stop condition is done using the MSE (Mean Square Error) criterion as shown in Equation (17).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{17}$$

MAPE is a percentage-based error metric that measures the average absolute percentage difference between the predicted values and the actual target values. It is particularly useful when dealing with data sets that have varying magnitudes. A lower MAPE value indicates better prediction accuracy. The forecasting value is said to be very good if the percentage error produced is less than 10% and is said to be good if the percentage error is between 10% and 20% (Zainun dan Majid, 2003) at [19].

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|X_i - F_i|}{X_i} \times 100\% \tag{18}$$

3. RESULTS AND DISCUSSION

3.1 Data Description

The data used in this study is secondary data, namely the open unemployment rate data of 2000 to 2022, sourced from the Central Bureau of Statistics of South Sulawesi Province, is shown in Table 1.

Table 1. Open Unemployment Rate in Makassar City, 2000-2022

No	Year	Open Unemployment Rate (%)
1.	2000	9.05
2.	2001	10.38
3.	2002	17.23
4.	2003	17.41
5.	**2004**	**18.13**
6.	2005	15.04
7.	2006	14.03
8.	2007	18
9.	2008	11.76
10.	2009	12.9
11.	2010	13.34
12.	**2011**	**7.16**
13.	2012	8.12
14.	2013	9.53
15.	2014	10.9
16.	2015	12.02
17.	2016	11.42
18.	2017	10.59
19.	2018	12.19
20.	2019	9.83
21.	2020	15.92
22.	2021	13.18
23.	2022	11.82

***Data source**: Website of the Central Bureau of Statistics (BPS) for South Sulawesi Province*

Overall, there are 23 data points from the year 2000 to the year 2022, where the highest open unemployment rate in Makassar City occurred in 2004 with a figure of 18.13%, and the lowest occurred in 2011 with an open unemployment rate of 7.16%, as shown in **Figure 7**.

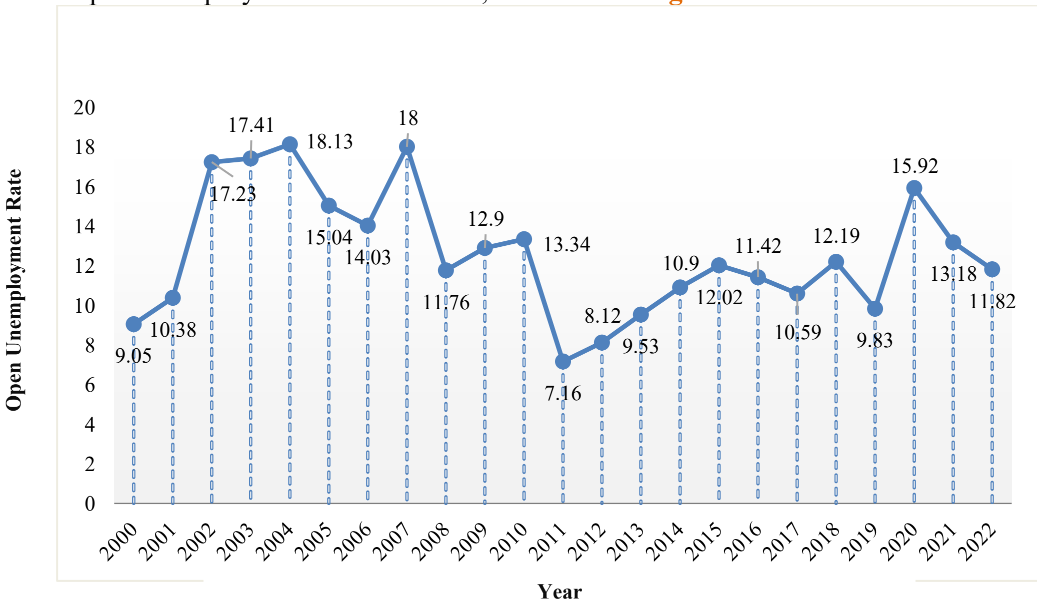

Figure 7. Open Unemployment Rate in Makassar City, 2000-2022

3.2 Data Preprocessing

The open unemployment rate data in **Table 1** is normalized to the interval [0.1 - 0.9] using the min-max scaling formula **Equation (19)**. This normalization is performed because the sigmoid activation function rarely reaches 0 or 1, and it also speeds up the training process **[23]**.

$$x' = \frac{0.8\,(x_i - \text{minimum value in the dataset})}{\text{maximum value in the dataset} - \text{minimum value in the dataset}} + 0.1 \tag{19}$$

The normalized data is presented in **Table 2**.

Table 2. Normalized Open Unemployment Rate Data for Makassar City

No	Year	Normalized Data	No	Year	Normalized Data
1.	2000	0.2378	13.	2012	0.1700
2.	2001	0.3348	14.	2013	0.2728
3.	2002	0.8344	15.	2014	0.3727
4.	2003	0.8475	16.	2015	0.4544
5.	2004	0.9000	17.	2016	0.4107
6.	2005	0.6747	18.	2017	0.3501
7.	2006	0.6010	19.	2018	0.4668
8.	2007	0.8905	20.	2019	0.2947
9.	2008	0.4355	21.	2020	0.7388
10.	2009	0.5186	22.	2021	0.5390
11.	2010	0.5507	23.	2022	0.4398
12.	2011	0.1000			

In the data preprocessing stage, the normalized open unemployment rate data is used as the input parameter **[2]**. The data is formed using Time Series Cross-Validation with Rolling Window, where the entire dataset is divided into subsets or folds of equal size K. Then, a model is trained on fold K - 1 (training set), and the remaining fold is used for model testing (testing set), as shown in **Figure 8 [24]**.

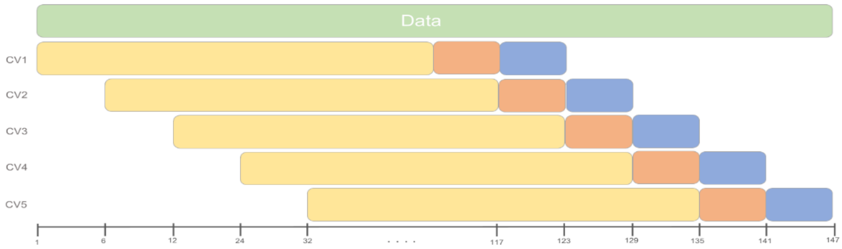

Figure 8. **Time Series Cross-Validation with Rolling Window Pattern [24]**

The data is formed into 11 time series data ($x_1, x_2, x_3, \dots, x_{11}$) and 1 as the target data, where 11 input data are 11 years of data and 1 output is 1 year after. The data division pattern or scheme is then created according to **Table 3**.

Table 3. **Data Division Scheme**

No	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	Target
1	Data 2000	Data 2001	Data 2002	Data 2003	Data 2004	Data 2005	Data 2006	Data 2007	Data 2008	Data 2009	Data 2010	Data 2011
2	Data 2001	Data 2002	Data 2003	Data 2004	Data 2005	Data 2006	Data 2007	Data 2008	Data 2009	Data 2010	Data 2011	Data 2012
3	Data 2002	Data 2003	Data 2004	Data 2005	Data 2006	Data 2007	Data 2008	Data 2009	Data 2010	Data 2011	Data 2012	Data 2013
…	…	…	…	…	…	…	…	…	…	…	…	…
10	Data 2009	Data 2010	Data 2011	Data 2012	Data 2013	Data 2014	Data 2015	Data 2016	Data 2017	Data 2018	Data 2019	Data 2020
11	Data 2010	Data 2011	Data 2012	Data 2013	Data 2014	Data 2015	Data 2016	Data 2017	Data 2018	Data 2019	Data 2020	Data 2021
12	Data 2011	Data 2012	Data 2013	Data 2014	Data 2015	Data 2016	Data 2017	Data 2018	Data 2019	Data 2020	Data 2021	Data 2022

Normalized open unemployment rate data for Makassar City from **Table 2** is substituted into **Table 3** resulting in **Table 4**.

Table 4. **Substitution of Open Unemployment Rate Values**

No	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	Target
1	0.2378	0.3348	0.8344	0.8475	0.9000	0.6747	0.6010	0.8905	0.4355	0.5186	0.5507	0.1000
2	0.3348	0.8344	0.8475	0.9000	0.6747	0.6010	0.8905	0.4355	0.5186	0.5507	0.1000	0.1700
3	0.8344	0.8475	0.9000	0.6747	0.6010	0.8905	0.4355	0.5186	0.5507	0.1000	0.1700	0.2728
4	0.8475	0.9000	0.6747	0.6010	0.8905	0.4355	0.5186	0.5507	0.1000	0.1700	0.2728	0.3727
5	0.9000	0.6747	0.6010	0.8905	0.4355	0.5186	0.5507	0.1000	0.1700	0.2728	0.3727	0.4544
6	0.6747	0.6010	0.8905	0.4355	0.5186	0.5507	0.1000	0.1700	0.2728	0.3727	0.4544	0.4107
7	0.6010	0.8905	0.4355	0.5186	0.5507	0.1000	0.1700	0.2728	0.3727	0.4544	0.4107	0.3501
8	0.8905	0.4355	0.5186	0.5507	0.1000	0.1700	0.2728	0.3727	0.4544	0.4107	0.3501	0.4668
9	0.4355	0.5186	0.5507	0.1000	0.1700	0.2728	0.3727	0.4544	0.4107	0.3501	0.4668	0.2947
10	0.5186	0.5507	0.1000	0.1700	0.2728	0.3727	0.4544	0.4107	0.3501	0.4668	0.2947	0.7388
11	0.5507	0.1000	0.1700	0.2728	0.3727	0.4544	0.4107	0.3501	0.4668	0.2947	0.7388	0.5390
12	0.1000	0.1700	0.2728	0.3727	0.4544	0.4107	0.3501	0.4668	0.2947	0.7388	0.5390	0.4398

3.3 Data Training and Testing Division

The data division in this study involves dividing the open unemployment rate data into two parts: training data and testing data based on the data scheme determined in the previous stage. This study uses 7 scenarios for dividing training and testing data, as shown in **Table 5**.

Table 5. Data Division Scenarios

Scenario	Training Data	Number of Training Data (Dataset)	Testing Data	Number of Testing Data (Dataset)
1	80%	**10**	20%	**2**
2	70%	**8**	30%	**4**
3	60%	**7**	40%	**5**
4	50%	**6**	50%	**6**
5	40%	**5**	60%	**7**
6	30%	**4**	70%	**8**
7	20%	**2**	80%	**10**

Based on **Table 5**, the training data is used as input data to train the predetermined network model by updating the initialized weights and biases until the specified iteration/epoch is reached and the training accuracy value is generated. The testing data is data that has never been used by the network model before and is therefore used as data to evaluate the network model and then generate the forecasting accuracy value.

3.4 Design of Artificial Neural Network Models

The Artificial Neural Network (ANN) method used to forecast the open unemployment rate in Makassar City is an ANN using the Backpropagation algorithm that has several layers, including an input layer, several neurons in the hidden layer, and an output layer.

The success in achieving the target in the Backpropagation method is highly influenced by the network model used. This is because each problem has different model requirements **[2]**. Therefore, several designs of the artificial neural network models used are shown in **Table 6**.

Table 6. Backpropagation ANN Model Design

Backpropagation ANN Model	Description
11 – 10 – 1	11 neurons in the input layer, 10 neurons in the hidden layer, 1 neuron in the output layer
11 – 28 – 1	11 neurons in the input layer, 28 neurons in the hidden layer, 1 neuron in the output layer
11 – 50 – 1	11 neurons in the input layer, 50 neurons in the hidden layer, 1 neuron in the output layer
11 – 55 – 1	11 neurons in the input layer, 55 neurons in the hidden layer, 1 neuron in the output layer

The selection of 11 input neurons is based on a rolling window approach in time series forecasting, where the unemployment rates from the previous 11 years are used to predict the subsequent year. This window size was chosen to balance between capturing long-term trends and maintaining a sufficient number of training samples. The output layer consists of a single neuron corresponding to the one-year-ahead forecast. The selection of the number of neurons in the hidden layer was guided by prior empirical studies that reported optimal network structures for time series forecasting problems. Specifically, the use of 10 hidden neurons was motivated by the findings of **[7]**, who demonstrated that a 10–10–1 architecture yielded the best forecasting performance with a learning rate of 0.1. The configuration with 28 hidden neurons was adapted from **[15]**, whose study employed a 4–28–1 structure for predicting regional meat production. Similarly, the 50-neuron configuration was based on **[22]**, where a 12–50–1 model was reported to achieve high accuracy in car sales prediction using a learning rate of 0.05. Lastly, the choice of 55 hidden neurons was derived from **[25]**, who implemented a 4–55–1 model for educational data forecasting with a learning rate of 0.01. These references were used as empirical benchmarks to explore whether similar configurations would yield optimal results for unemployment rate forecasting in this study.

The best model is determined through a trial-and-error process until a model with the lowest MSE value and the best accuracy level based on the data pattern division scenarios for training and testing data is obtained. After the architecture of the artificial neural network is determined, training is then carried out based on the previously determined training scenario.

3.5 Training and Testing of the Artificial Neural Network

3.5.1 Network Training Process

Based on the data division scenario in Table 5, this study uses seven scenarios for dividing training and testing data. The number of epochs used is 1000 epochs with the use of varying learning rate values of 0.05, 0.01, 0.1, and 0.5, which aims to obtain more accurate forecasting results.

The network training process is divided into 3 stages, namely the weight initialization stage, the feedforward stage, and the last stage, which is the backward stage. The results of network training for each scenario are as shown in Table 7.

Table 7. Best Network Model based on Data Division Scenario

Data Division Scenario	Number of hidden layer neurons	*Learning rate*	*Epoch*	Result	
				MSE	MAPE (%)
80:20	55	0.5	214	0.000999	9.5313
70:30	10	0.5	1000	0.0012	8.9965
60:40	10	0.5	253	0.000998	8.9168
50:50	55	0.1	533	0.000994	10.6482
40:60	28	0.5	113	0.000998	11.0219
30:70	55	0.5	125	0.000949	11.0716
20:80	28	0.5	58	0.000943	20.3774

Based on the table, it can be seen that the scenario 1 architecture (11 – 55 – 1) with 80% training data and 20% testing data with learning rate = 0.5 is the best scenario in network training because it has the lowest MSE value of 0.000999. Although the MAPE value produced is higher (9.5313%) compared to scenario 3 (8.9168%), the number of epochs produced to achieve the target error that has been determined is less (214 Epoch) compared to scenario 3 (253 Epoch). The results of the training carried out on the *Matlab software* are as shown in Figure 9.

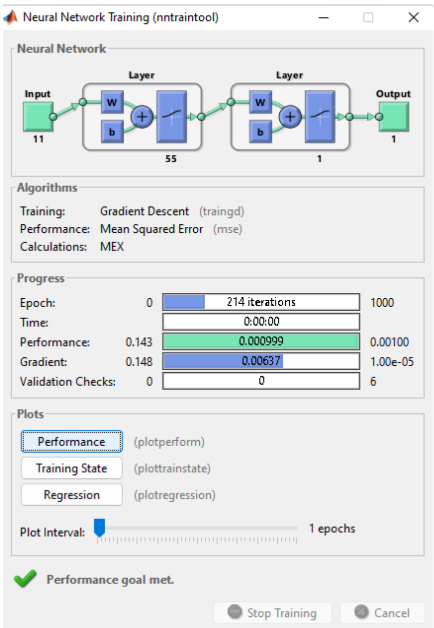

Figure 9. Scenario 1 Network Training Results, Learning Rate 0.5

Based on Figure 9, the results of the JST backpropagation process which includes the entire training process can be found.

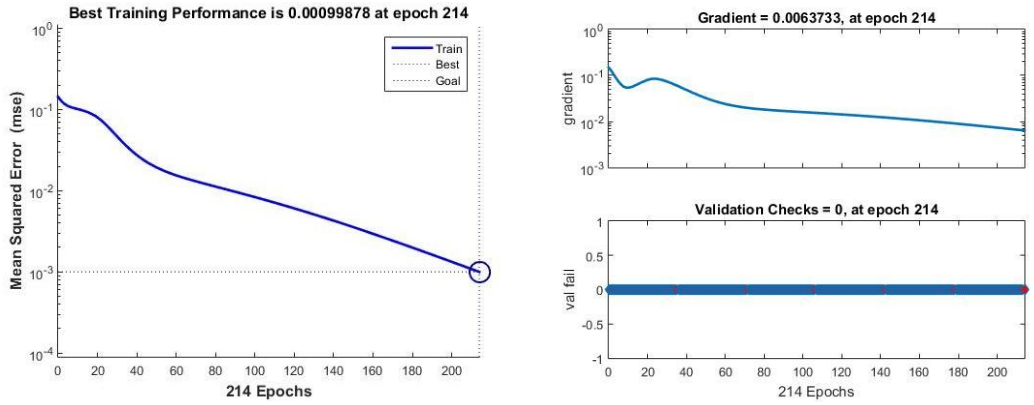

Figure 10. Plot of Scenario 1 *Learning rate* 0.5. (a) Learning Process Result, (b) Train State Plot

In **Figure 10** shows the graph displayed after the training process using scenario 1 with *learning rate* = 0.5. **Figure 10** (a). shows the learning process at each epoch. At this stage, the iteration is stopped at the 214th epoch, because the desired epoch limit has been reached MSE=0.00099878, where this MSE is the value that appears when the training is completed according to the specified iteration or when it reaches the target value. In **Figure 10** (b). shows the train state with a gradient of 0.0063733 at the 214th epoch and validation checks of 0 at the 214th iteration.

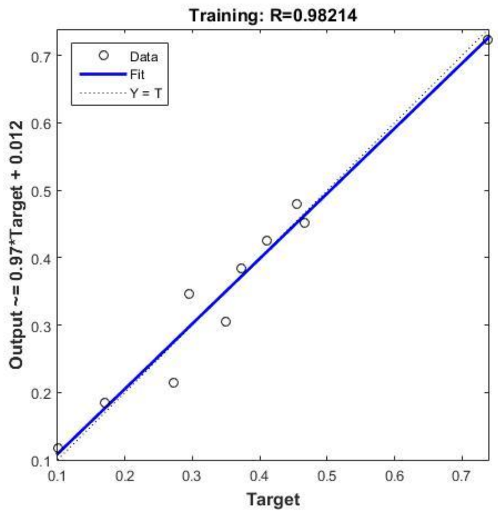

Figure 11. Correlation Coefficient Plot Scenario 1 with *Learning rate* 0.5

Based on **Figure 11**. The test on the training data shows the relationship between the target and the network output. The results show that the correlation coefficient (R) is 0.98214, which is close to the optimal value of 1. The correlation coefficient (R) that almost reaches the optimal number indicates that the network has been able to forecast well according to the existing data.

3.5.2 Network Testing and Evaluation

After the training process, the best network model in each scenario will undergo the testing or evaluation stage to evaluate its performance. The purpose of this evaluation is to assess how well the trained network performs. The results of this evaluation are then used to determine the most optimal and effective network model for use in forecasting or related tasks. In the testing stage, the weights used are the final weights generated in the training process, then testing is carried out with the feedforward stage to obtain the output results.

The results of testing and evaluating the best network model in each scenario can be seen in **Table 8**.

Table 8. Results of Testing and Evaluating Each Scenario Model

Data Division Scenario	Architecture Model	Result	
		MSE	MAPE(%)
80:20	11-55-1	0.0029	8.1309
70:30	11-10-1	0.0225	34.0584
60:40	11-10-1	0.0277	34.9533
50:50	11-55-1	0.0846	49.9053
40:60	11-28-1	0.0775	45.3532
30:70	11-55-1	0.1019	62.6590
20:80	11-28-1	0.0652	50.7572

Table 8 shows that the network with the 11-55-1 model in the first scenario obtained the best MAPE accuracy of 8.1309% or an average forecasting success rate of 91.8691% and the lowest MSE with a value of 0.0029. Based on the level of accuracy obtained, it can be said that the level of accuracy of the network model for forecasting the open unemployment rate in this study is very accurate so that the network model is feasible and adequate for use in forecasting.

The outputs generated by the training and testing process in the best scenario (80% training data and 20% test data, *learning rate* = 0.5) can be seen and **Table 9** and **Table 10**.

Table 9. ANN Output Value and Target Value (Actual) Training Process

No.	Target	*Output*
1.	0.1000	0.1178
2.	0.1700	0.1842
3.	0.2728	0.2142
4.	0.3727	0.3844
5.	0.4544	0.4793
6.	0.4107	0.4253
7.	0.3501	0.3058
8.	0.4668	0.4509
9.	0.2947	0.3456
10.	0.7388	0.7228

Forecasting using the average absolute percentage error (MAPE) with a formula based on **Equation (18)** obtained MAPE = 9.5313% or it can be said that the average prediction/forecasting success is 90.4687%. The resulting output value can be seen in **Figure 12**.

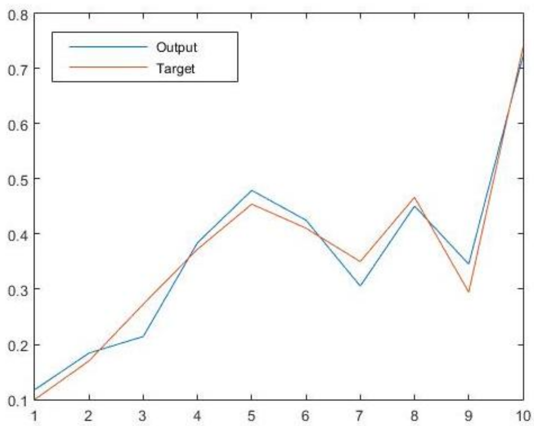

Figure 12. Plot of the Comparison between Backpropagation Prediction Values and Actual Values of the Training Process

Based on **Figure 12**, shows the comparison between the original target and the Backpropagation output on the training data with learning rate $(\alpha) = 0.5$, it can be seen that the comparison graph is not much different from each other. Furthermore, the output generated in the testing process can be seen in the following table.

Table 10. ANN Output Values and Target Values (Actual) Testing Process

No.	Target Test	*Output*
1.	0.5390	0.6138
2.	0.4398	0.4294

Forecasting using the mean absolute percentage error (MAPE) with the formula based on **Equation (18)** obtains MAPE = 8.1309% or it can be said that the average prediction/forecasting success rate is 91.8691%. The output values that are generated can be seen in **Figure 13**. However, a key limitation of this study is the absence of benchmark comparisons with other widely used forecasting methods, such as ARIMA, Support Vector Machines (SVM), or Long Short-Term Memory (LSTM) networks. Without such comparative analysis, the generalizability and relative effectiveness of the proposed Backpropagation ANN model cannot be fully assessed. Future studies are encouraged to implement and evaluate alternative models on the same dataset to establish a more comprehensive understanding of the model's robustness and practical relevance.

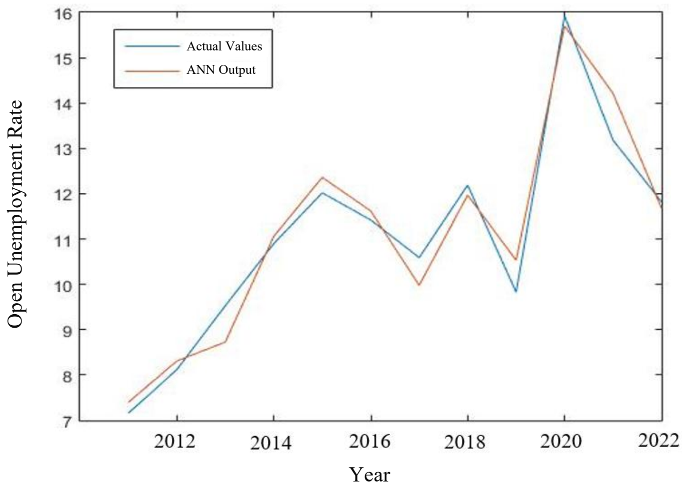

Figure 13. Plot of Comparison between Actual Values and ANN Output

Figure 13 shows the comparison between the open unemployment rate forecast using the artificial neural network with the actual open unemployment rate from the South Sulawesi Statistics Agency, which shows that the comparison graph is not much different from each other, indicating that the Backpropagation artificial neural network can forecast the open unemployment rate in Makassar City very well.

3.6 Forecasting of Open Unemployment Rate in Makassar City

After going through the training and testing stages, the best network model (11-55-1) is obtained and used to forecast the open unemployment rate in Makassar City for the next 5 years, starting from 2023. The forecasting results are obtained through processing with Matlab 2015a software as shown in **Table 11**.

Table 11. Forecasting Results of Open Unemployment Rate in Makassar City

Year	Forecasting Result with Backpropagation
2023	0.2399
2024	0.2093
2025	0.1419
2026	0.1318
2027	0.1064

The results shown in **Table 11** are still in decimal form. To obtain the real-world values, the results need to be denormalized using **Equation (20)**.

$$x'' = \frac{x' - (0{,}1)}{0{,}8}\,(\text{maximum value} - \text{minimum value}) + \text{minimum value} \tag{20}$$

The denormalized values are shown in **Table 12**.

Table 12. Open Unemployment Rate in 2023-2027 after Denormalization

Year	Denormalized Forecasting Result (%)
2023	9.0784
2024	8.6588
2025	7.7346
2026	7.5961
2027	7.2478

Based on the denormalized results in **Table 12**, it can be observed that the open unemployment rate in Makassar City is projected to decrease in each year from 2023 to 2027. indicating a positive trend in the city's employment situation. These findings have important implications for local policymakers. The projected downward trend suggests that current labor policies may be yielding results; however, sustained improvement requires strategic reinforcement. Forecasting models such as this can serve as an early warning system, enabling city authorities to allocate resources more efficiently, implement targeted employment programs, and anticipate labor market needs. Specifically, the government could use these insights to design or adjust vocational training, job creation initiatives, and support for sectors expected to absorb future labor demand.

4. CONCLUSION

The Backpropagation artificial neural network (ANN) method has been successfully applied to forecast the open unemployment rate in Makassar City for the next 5 years. After the analysis process was carried out, the Backpropagation ANN model with the best forecasting accuracy was obtained using 11 neurons in the input layer, 55 neurons in the hidden layer, and one neuron in the output layer with a learning rate of 0.5. The results show that the ANN model can accurately predict the unemployment rate with a MSE value of 0.003 and an MAPE value of 9.531% with a proportion of 80% training data and 20% test data, which is the best among all data division scenarios. The denormalized results reveal a downward trend in the open unemployment rate from 2023 to 2027, indicating a positive employment outlook in Makassar City.

Despite these promising results, this study has several limitations. The absence of benchmark comparisons with other forecasting methods such as ARIMA, SVM, or LSTM limits the ability to generalize the model's superiority. Additionally, the model does not incorporate external variables that may influence unemployment trends, such as economic shocks or policy interventions.

Future research should focus on comparative analysis with other statistical and machine learning models to validate and enhance forecasting performance. Incorporating exogenous variables (e.g., inflation rate, education level, or labor policies) and employing advanced optimization techniques such as Bayesian Optimization or Genetic Algorithms may also improve model robustness and interpretability. Moreover, expanding the model to other regional datasets could support broader applications for public policy and planning.

AUTHOR CONTRIBUTIONS

Rahmat Syam: Conceptualization, Methodology, Supervision, Writing-Review and Editing. Sahlan Sidjara: Methodology, Supervision, Validation, Writing-Review and Editing. Adib Roisilmi Abdullah: Conceptualization, Data Curation, Software, Formal Analysis, Investigation, Visualization, Writing- Original Draft. All authors discussed the results and contributed to the final manuscript.

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CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this research.

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