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PERFORMANCE OF THE ACCURACY OF FORECASTING THE CONSUMER PRICE INDEX USING THE GARCH AND ANN METHODS

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ABSTRACT

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The Consumer Price Index (CPI) is the most widely used indicator of the inflation rate. Then, the value of CPI in the future must be known to be the basis of the government's making appropriate and accurate policies. The CPI data used in this study was taken from the Central Statistics Agency (BPS) from January 2006 - to December 2021. The CPI data used has a data pattern containing symptoms of heteroskedasticity. To overcome the symptoms of heteroskedasticity, the author uses the GARCH and ANN methods to determine the value of CPI in the future. The GARCH method can overcome the symptoms of heteroskedasticity in the time series forecasting process, while ANN is an effective method in time series forecasting because of its high level of accuracy. In this study, MAPE calculation results were obtained with the ARIMA model (4,2,2)~GARCH(1.1) of 3.19% or with an accuracy of 96.81%, and ANN using two hidden layers of 1.24% or with an accuracy of 98.76%. Thus, the results of this study show that the ANN method is the best method of forecasting Consumer Price Index (CPI) data.

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1. INTRODUCTION

The Consumer Price Index is an indicator used to measure the inflation and deflation of a group of goods and services in general. CPI forecasting becomes vital as early detection in the face of price spikes [1]. CPI is critical because the cpi value is a widely used indicator of the inflation rate. So, research to find out the value of the upcoming CPI needs to be done so that the government or authorized institutions can control the value of inflation.

In the case of encountering the type of data with conditions that tend to indicate the presence of heteroskedasticity, special handling is needed to analyze the data. The variance of variable errors occurs because the variance of errors depends not only on the free variable but also on how big the square of the error was in the previous period [2]. According to [3], this GARCH model has the potential to avoid too high a lag on the ARCH model based on the principle of parsimony or choose a simpler model, so it will ensure the variance is always positive.

The Artificial Neural Network method is one of the artificial intelligence methods that can identify patterns, signal processing, and forecasting of the system with an excellent learning method of time series forecasting [4]. The advantage of neural networks is that optimal results are obtained compared to other conventional time series forecasting methods, both long-term and accurate. The Artificial Neural Network method provides accurate predictions and widely forecasts time series data. The Artificial Neural Network method can be used for forecasting because it can conclude correctly even though the data contains noisy information [5].

Referring to a previous study by [6] entitled "Application of Artificial Neural Network Methods in Forecasting the Number of Visits of Pregnant Women (K4)" obtained an average percentage of errors based on comparison with actual data is 0.1854 or an accuracy of 99.81 per cent. So the study concludes that the artificial neural network method has a low error value and good accuracy. Furthermore, the study studied by [7] entitled "Application of ARCH GARCH Method in Forecasting Consumer Price Index (CPI in Semarang City" obtained the best model ARIMA (1,1,1) ~GARCH(1.0) with predictions of volatility with a standard deviation value of 0.98. Then the study studied by [8] entitled "Comparison Of Stock Prediction With Generalized Autoregressive Conditional Heteroscedasticity Model And Artificial Neural Network" obtained the results of error calculations in RMSE forecasting with GARCH model (1.0) of 0.3234 and ANN using 21 hidden layers of 0.0091. Research on Artificial Neural networks was also conducted by [9] entitled "Daily Electrical Load Forecasting Using Artificial Neural Network", which obtained a MAPE value from ANN network structure of 7.6%. Research reviewed by [10] entitled "Application of ARCH/GARCH Model for Farmer Exchange Rate Forecasting" obtained by ARCH(1) model with MAPE value of 3.64.

With various forecasting methods and the development of forecasting methods with time-guided data that is relatively rapid, many methods can be used. That is done according to needs, and it is necessary to compare one method with another to get the forecast results with a high accuracy value. Based on the description, the author is interested in submitting a study titled "Performance of The Accuracy of Forecasting Consumer Price Index using the GARCH and ANN Methods".

2. RESEARCH METHODS

2.1 Time and Place of Research

This research was conducted in the odd semester of 2021/2022 and is located in the Department of Mathematics, Faculty of Mathematics and Natural Sciences, University of Lampung.

2.2 Research Data

The Indonesian CPI data from the BPS was taken from January 2006 to December 2021.

2.3 Research Methods

This research was conducted using systematic literature studies obtained from books and media to get as much information as possible to support the writing of this thesis. The processing of such data is carried out using R-studio software.

The steps taken in this study are as follows:

1. Take data from the Indonesian CPI on the Indonesian Central Statistics Agency website.
2. Conducting ARIMA assumption tests, then continue with the ARIMA modeling process using R-Studio software
   a. Identify the plot
   b. Perform stationarity tests
   c. Transforming and differencing if needed
   d. Estimate the parameters of the ARIMA model and determine the best ARIMA Model,
   e. Perform an ARCH effect test
3. Performing GARCH modeling
4. Perform forecasting with the GARCH model.
5. Scaling data.
6. Conduct training and testing of CPI data.
7. Build a neural network model.
8. View the accuracy and validation of the formed model.
9. Perform forecasting with the best ANN network structure.
10. Determine the best model based on the smallest MAPE value.

Briefly, the forecasting process with the GARCH model using R-Studio software is as follows:

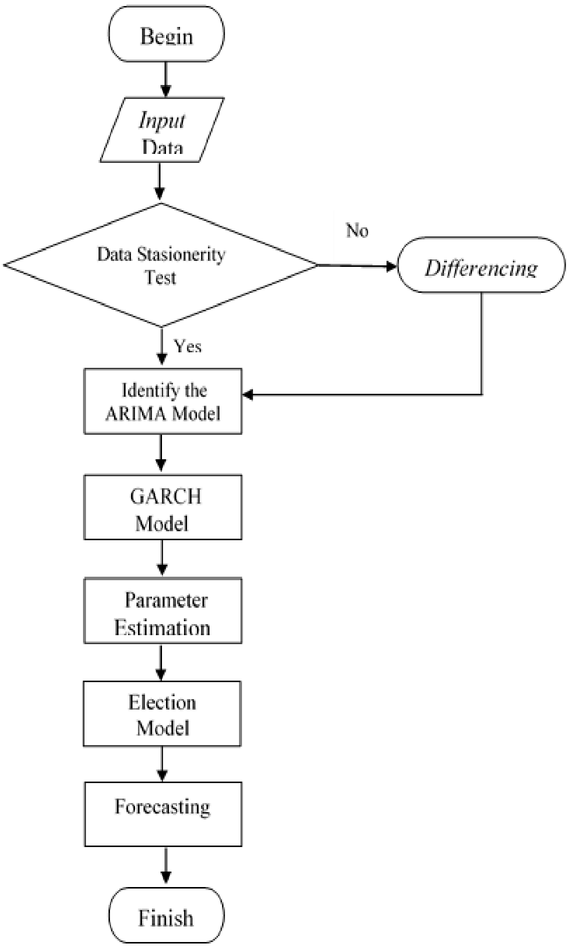

Figure 1. GARCH Process *Flowchart*

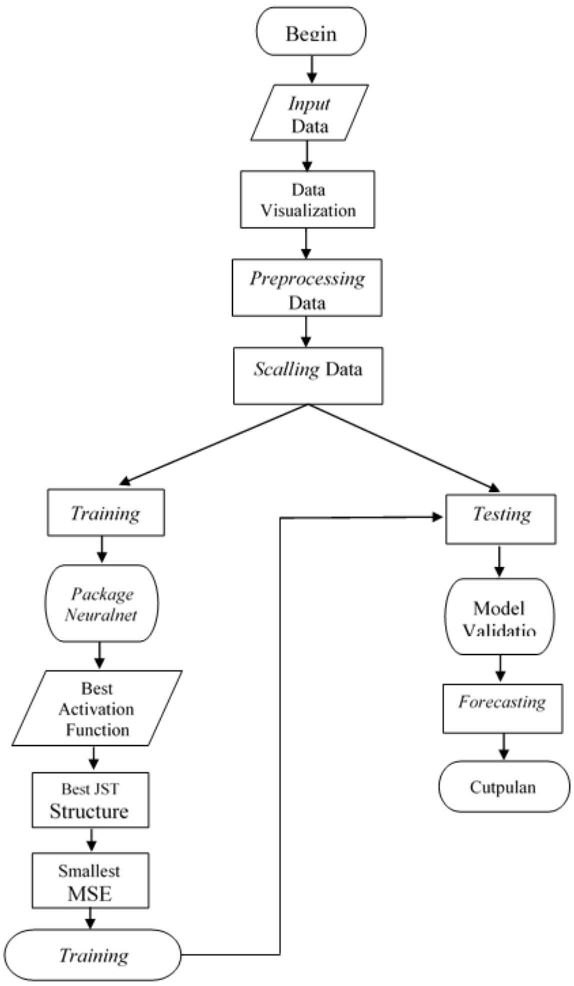

Figure 2. ANN Process *Flowchart*

2.4 Forecasting

Forecasting is an estimate of future values or conditions. A common assumption used in forecasting is that past patterns will continue. Forecasting predicts a changer's values to the value known by the changer. Fortune-telling can also be based on scoring expertise based on historical data and experience [11].

2.5 Time Series Data

Time series data is collected according to the time rules in a given period. The collection frequency is always the same if time is viewed as discrete (time can be modeled as continuous). The frequency can be seconds, minutes, hours, days, weeks, months, or years [12].

2.6 ARIMA Time Series Model

According to [13], there are several Box-Jenkins [14] models used to analyze time-series data, namely:

1. Model Autoregressive (AR)
   The general form of the autoregressive model with the order p (AR) or the ARIMA model (p,0,0) is expressed as follows:
   $$Y_t = \mu + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p + e_t Y_{t-p} \quad (1)$$

2. Model Moving Average (MA.)
   The general form of the moving average model order q (MA) or ARIMA (0,0,q) is expressed as follows:
   $$Y_t = \mu + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-k} \quad (2)$$

3. Model Autoregressive Moving Average (ARMA)
   The general model for a mixture of pure AR(1) and pure MA(1) processes, e.g. ARIMA (1,0,1), is expressed as follows:
   $$Y_t = \mu + \phi_1 Y_{t-1} + e_t + \theta_1 e_{t-1} \quad (3)$$

4. Model Autoregressive Integrated Moving Average (ARIMA)
   The common forms of the ARIMA model (p,d,q) are:
   $$Y_t^* = \mu + \phi_1 Y_{t-1}^* + \phi_2 Y_{t-2}^* + \cdots + \phi_p Y_{t-p}^* + \mu_t + \theta_1 \mu_{t-1} + \cdots + \theta_q \mu_{t-q} \quad (4)$$

2.7 Generalize Autoregressive Conditional Heteroskedasticity (GARCH)

The GARCH method (p, q) develops the Autoregressive Conditional Heteroskedasticity (ARCH) model. This model was developed to avoid too high an order on the ARCH model by choosing a simpler model to guarantee that the variance is always positive [3].

According to [15] , the general form of the GARCH model (p, q) is:

$$Y_t = b_0 + b_1 X_t + \varepsilon_t$$

$$\sqrt{\alpha_0 + \sum_{i=1}^{p} \alpha_i e_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2}$$

$$\sigma_t^2 = \alpha_0 + a_1 e_{t-1}^2 + \cdots + \alpha_p e_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_q \sigma_{t-q}^2 \quad (5)$$

2.8 Artificial Neural Network (ANN)

Artificial Neural Networks are one of the artificial representations of the human brain that always tries to simulate the process of exploration in the human brain. Pandjaitan [16] defines ANN as a computational technology based on biological neural models and tries to simulate the behavior and work of neural models against various inputs. Both biological neural networks and ANN are units of information processing.

There are several types of ANN, but they all have the same components. Like the human brain, neural networks are made up of several neurons (often called nodes), and each neuron is connected and performs information processing as in biological neural network systems. Biological nerves (neurons) have three crucial components: dendrite, nucleus, and axon. Dendrite receives signals from other neurons. The signal is modified (amplified/weakened) by synapse gaps. Next, the nucleus sums up all incoming signals. If the amount is strong enough and exceeds the threshold, the signal will be passed to other neurons through the axon [17].

2.9 Model Validation

According to [18] , a forecasting technique that uses quantitative data with data at a particular time, there are errors/errors generated by the technique. Consequently, a method is needed to measure how many errors can be generated by the forecasting method to be reconsidered before making a decision. Methods that can be used in evaluating errors in forecasting techniques are MSE (Mean Square Error), RMSE (Root Mean Square Error), MAD (Mean Absolute Derivation), MAPE (Mean Absolute Percentage Error) and MPE (mean percentage error).

[19] state that forecasting is successful when producing low MAPE. Table 1. indicates the description of each MAPE value

Table 1. MAPE Value Criteria

No.	MAPE (%)	Value Explanation
1	<10	Excellent
2	10-20	Good
3	20-50	Keep
4	>50	Bad

3. RESULTS AND DISCUSSION

This study will be outlined the performance of GARCH and ANN methods in forecasting the CPI. The GARCH method is one of the time series forecasting methods that can overcome the symptoms of heteroscedasticity in CPI data. So when the heteroscedasticity problem is resolved, a model and forecasting of CPI data will produce good accuracy. In addition to the GARCH method, this study will use ANN's renewable time series forecasting method. The ANN method is a method that can create the best network structure to forecast CPI data.

3.1. Identify plots

Stationary can be proven by looking at the plot and root test values of The Dickey-Fuller Augmented unit (ADF) as follows:

Table 2. ADF Test Results Consumer Price Index Data

Dickey-Fuller	Lag order	p-value
-2.8857	5	0.206

From Table 2, it can be known whether the CPI data is stationary or has not used the following hypotension test:

H_0 : CPI data is not stationary
H_1 : stationary CPI data

Based on the ADF test obtained value, the decision is not rejected H_0, or the data is not stationary. Furthermore, the data needs to $p - value > \alpha = 0.05$ be differencing to become stationary.

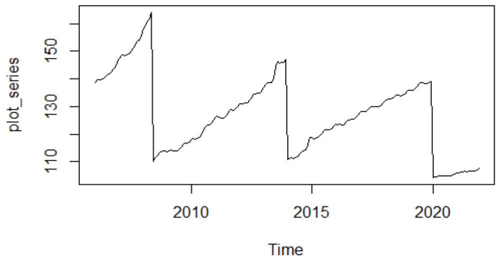

Figure 3. Consumer Price Index Data Plot

Based on **Figure 3**, it appears to contain trend elements, meaning that the data is not stationary. Then it can be concluded that the residual variant of this time series data has not been constant, varies from one period to another, and may contain elements of heteroskedasticity. After the second differencing process, the data is retested with the ADF Test and seen plot after the second differencing.

Table 3. ADF Test Results from Consumer Price Index Data after being Second Differencing

Dickey-Fuller	Lag order	p-value
-9.363	5	0.01

From **Table 3**, it can be known whether the CPI data is stationary or has not used the hypothesis test as follows:
H_0 : CPI data is not stationary
H_1 : stationary CPI data

Based on the ADF test obtained value, then the decision to reject H_0. Alternatively, in other words, the data has been stationary $p - value \ < \ \alpha = 0.05$

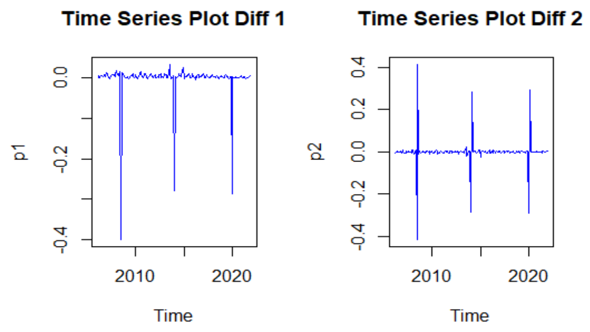

Figure 4. Consumer Price Index Data Plot after *Differencing*

Based on **Figure 4**, the data's movement has moved up and down around the average and does not contain a trend user, meaning that the data has been stationary against the mean. Thus the data is stationary to the mean and variance, and then the assumptions in the Box-Jenkins (ARIMA) method are fulfilled. So that the following process can be done in the stages of time-guided data analysis using the Box-Jenkins (ARIMA) method.

3.2. Identify the ARIMA Model

The identification stage is a stage used to find or determine ARIMA parameters (p, d, q) using the ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots. With p is an AR model identified using a PACF plot, d is the number of differencing performed when discussing data, i.e. twice, and q is the MA model identified from the ACF plot. Here is a graph of ACF and PACF using R-Studio software:

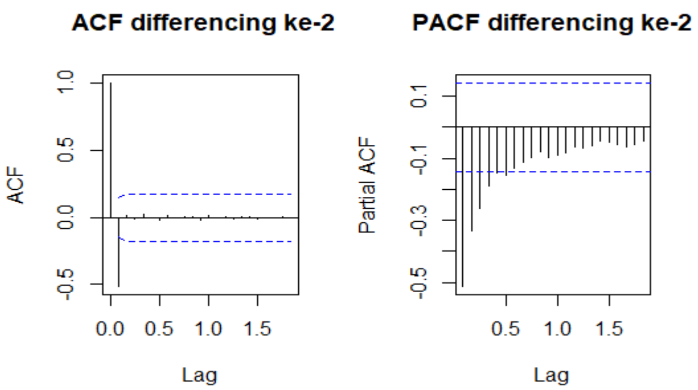

Figure 5. The plot of ACF and PACF

Based on **Figure 5**, it can be seen that 2 Project Lines pass significance limits on ACF, which means the order q is 2, and 4 Project Line passes significance limits on PACF, which means order p is four and d is 2 (the number of differencing what is done). Thus the initial model formed is the ARIMA model (4, 2, 2). Other relevant models formed from early models are the ARIMA models (4, 2, 1), (4, 2, 0), (3, 2, 2), (3, 2, 1), and (3, 2, 0).

3.3. Estimated Parameters of the ARIMA Model

The ARIMA model has been identified, and the parameter estimation has been carried out. The method used for parameter estimation is the least square (smallest square). The least-square method can guess the ARMA parameters, namely AR (φ) and MA (θ). Then after the estimation of the parameters, it is necessary to know whether the parameters can be included in the model by using the hypothesis test. A significant model is a model that has a P-value value < α in the Final Estimation of Parameters.

Table 4. ARIMA Model ARIMA Parameter and Value Estimation Decision

Model ARIMA	Type Parameter	Coef	P-*value*	Decision	AIC
(4, 2, 2)	AR 1	-0.80	2.2×10^{-16}	Significant	-588.09
	AR 2	-0.58	5.1×10^{-11}		
	AR 3	-0.38	1.4×10^{-05}		
	AR 4	-0.17	0.01		
	MA 1	-1.99	2.2×10^{-16}		
	MA 1	0.99	2.2×10^{-16}		
(4, 2, 1)	AR 1	-1.34	2.2×10^{-16}	Significant	-520.30
	AR 2	-1.20	2.2×10^{-16}		
	AR 3	-0.80	4.6×10^{-15}		
	AR 4	-0.33	1.1×10^{-06}		
	MA 1	-1.00	2.2×10^{-16}		
(4, 2, 0)	AR 1	-1.72	2.2×10^{-16}	Significant	-415.63
	AR 2	-1.72	2.2×10^{-16}		
	AR 3	-1.16	2.2×10^{-16}		
	AR 4	-0.43	1.1×10^{-11}		
(3, 2, 2)	AR 1	-0.75	2.2×10^{-16}	Significant	-584.35
	AR 2	-0.48	2.2×10^{-09}		
	AR 3	-0.24	0.000		
	MA 1	-1.99	2.2×10^{-16}		
	MA 1	0.99	2.2×10^{-16}		
(3, 2, 1)	AR 1	-1.20	2.2×10^{-16}	Significant	-500.17
	AR 2	-0.90	2.2×10^{-16}		
	AR 3	-0.40	7.1×10^{-10}		
	MA 1	-0.99	2.2×10^{-16}		
(3, 2, 0)	AR 1	-1.34	2.2×10^{-16}	Significant	-376.71
	AR 2	-1.20	2.2×10^{-16}		
	AR 3	-0.80	4.6×10^{-15}		
	AR 4	-0.33	1.1×10^{-06}		
	MA 1	-1.00	2.2×10^{-16}		

Table 4 shows that the ARIMA model (4, 2, 2) is the best mode because it has the smallest AIC value.

3.4. Generalize Autoregressive Conditional Heteroskedasticity Model Identification

After obtaining the best ARIMA model, then the GARCH model identification stage. It will be done with the ARCH effect approach and determining orders from GARCH by looking at the residual square's ACF and PACF correlogram plots.

Before modeling CPI data from January 2006 to December 2021 with GARCH, it will first be tested to determine whether the ARMA model (4.2) for CPI data from January 2006 to December 2021 has an ARCH effect. Testing is done with the ARCH Lagrange Multiplier test with the help of R-Studio software. The null hypothesis and the alternative hypothesis are as follows:

$$H_0 = \lambda_1 = \lambda_2 = \cdots = \lambda_q = 0$$
$$H_1 = \lambda_1 \neq 0 \; atau \; \lambda_2 \neq 0 \; atau \ldots atau \; \lambda_q \neq 0 \quad (6)$$

Table 5. Lagrange Multipier Test

Order	LM	p-value
4	1153	0.00
8	521	0.00
12	317	0.00
16	215	0.00
20	154	0.00
24	113	6.4×10^{-14}

3.5. Knowledge Discovery in Database (KDD)

After obtaining the best GARCH model, the author will again explore knowledge by applying a neural network with a backpropagation algorithm to the data that has been obtained. The data obtained is still raw data that cannot be processed directly. The library review states that the data must still be processed using KDD rules. The data in the table below is only an overview of the overall data. The data to be used is CPI data for 16 years, amounting to 192. After obtaining the best Artificial Neural Network network structure, the author will compare the accuracy of the GARCH and ANN methods in forecasting consumer price index data.

3.5.1. Data Selection

Determining the input used is the first step in finding a neural network model. The study used 16 years of Consumer Price Index data from January 2006 to December 2021 as input from neural network processes.

Table 6. Preliminary Data

Moon	IHK
January 2006	138.72
February 2006	139.53
March 2006	139.57
April 2006	139.64
May 2006	140.16
June 2006	140.79
July 2006	141.42
August 2006	141.88
September 2006	142.42
October 2006	143.65
November 2006	144.14
December 2006	145.89
January 2021	105.95
February 2021	106.06
March 2021	106.15
April 2021	106.29
May 2021	106.63
June 2021	106.46
July 2021	106.54
August 2021	106.57
September 2021	106.53
October 2021	106.66
November 2021	107.05
December 2021	107.66

3.5.2. Preprocessing Data

The next step is data preprocessing; there are several stages: converting data into a time series format, looking at the Partial Autocorrelation (PACF) plot, and looking at missing data.

1. Convert Data into Time-series Format

Data inputted into R-Studio will be converted into a time-series format. Once converted into a time series format, the data will be visualized in plot form to find the data pattern. In **Figure 6**, it can be seen that the data has a trend pattern.

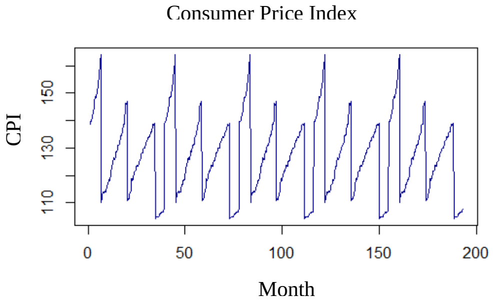

Figure 6. CPI Data Plot

2. Partial Autocorrelation Function (PACF)

An easy way to find out the number of past observations is to use PACF. The PACF is a function to measure the degree of strength when the influence is considered separate.y_t and y_{t+k} time lag $1,2,\dots,k-1$

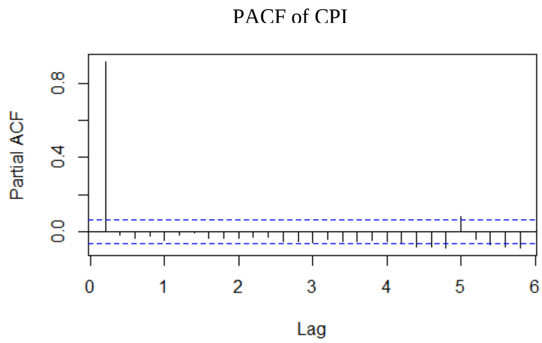

Figure 7. CPI Data PACF Plot

Figure 7 shows that lag 1 is significant on the PACF plot and insignificant on the subsequent lag (the value is still inside the interval/horizontal line).

Based on the PACF plot, the first lag data will be used in the neural network process. Data with k =1 is indicated in **Table 7**.

Table 7. Data *lag* k=1

	Was. 1	Data
Jan 2006	ON	138.72
February 2006	138.72	139.53
…	…	…
November 2021	106.66	107.05
December 2021	107.05	107.66

3. Missing Data

Data with lag 1 has some missing data or some data missing in the 1st row, and data analysis will be challenging if using an incomplete dataset. Thus, missing data is deleted by eliminating the first row in the lag data column 1.

Table 8. Dataset without *Missing* Data

	Was. 1	Data
February 2021	138.72	139.53
March 2021	139.53	139.57
…	…	…
November 2021	106.66	107.05
December 2021	107.05	107.66

3.5.3. Scaling Data

In KDD, there is a data transformation process to change the scale of measurements from the original form into other forms so that the data can be used for analysis and certain assumptions. In this study, the authors used one type of data scaling, namely min-max normalization. Here are the results of the min-max normalization of CPI data with the help of R-Studio software.

```
     Lag.1               data
 Min.   :0.0000   Min.   :0.0000
 1st Qu.:0.1830   1st Qu.:0.1776
 Median :0.3750   Median :0.3715
 Mean   :0.3819   Mean   :0.3814
 3rd Qu.:0.5498   3rd Qu.:0.5454
 Max.   :1.0000   Max.   :1.0000
```

Figure 8. Summary Min-Max Normalization

Figure 8 shows that the min-max normalization process produces a value at the interval [0.1] on each lag and original data. The mean value in the first lag was 0.3819, and the original data was 0.3814. No significant distance exists between the minimum value, quartile 1, median, mean, quartile 3, and the maximal value lag and the original data.

3.5.4. Training and Testing Data

After the scaling process is complete, the following process divides the original data into two parts: training data and data testing. The most widely used data composition is 50% for training and 50% for testing, 75% for training and 25% for testing, and 80% for training and 20% for testing. The 192 data will be divided into 75% training data and 25% testing data (144 training data and 48 data testing). Previously, the author used 80% of the data for training and 20% for testing, but the resulting error value was more significant than 75% for training data and 25% for data testing.

Table 9. Data *Training* and *Testing Error* Value

Training	Testing	Error
50%	50%	0.5730
80%	20%	0.4955
75%	25%	0.4954

Based on **Table 9**, it can be concluded that the use of 75% of training data and 25% of data testing is better used in ANN analysis compared to 50% of training data and 50% of testing data and 80% of training data and 20% of testing data.

3.6. *Hidden layer*

One of the essential components in building a neural network is the number of hidden layers and nodes in each hidden layer. Based on Healton's rules (2017), the author uses two hidden layers with one input node and one output node. Previously the author also tried to use one hidden layer, but the error results showed that using 2 hidden layers resulted in a smaller error value than 1 hidden layer.

Table 10. Hidden layer Usage Error Comparison

Number of Hidden Layers	Number of Nodes in the hidden layer	Error
1	1	0.5774
1	2	0.5774

Number of Hidden Layers	Number of Nodes in the hidden layer	Error
2	1	0.5775
2	2	0.4954

Table 10 shows that 2 hidden layers and 2 nodes in each hidden layer are better used in CPI practice because it has a small error value.

3.7. Threshold

There are similarities in neural networks with biological neuron cells in the human brain. Information on neuron cells, called inputs, will be transmitted to other neurons with a certain weight. This input will be processed by a function that will sum the values of all the weights and bounds. The activation function will then compare this sum with a specific threshold value. If the indigo in the input passes a particular threshold value, the neuron will be activated, and vice versa. In this study, the author will use a threshold value of 0.01 because the threshold value can produce a small MSE value in building a neural network. The smallest MSE is obtained using the Leaky ReLu activation function with two nodes in the first and second hidden layers.

3.8. Building a Neural Network using Backpropagation Algorithms

The neural network model network structure with a backpropagation algorithm built using the Leaky ReLu activation function, min-max normalization, threshold of 0.01 and 2 hidden layers containing two nodes will be used as a consumer price index forecasting model.

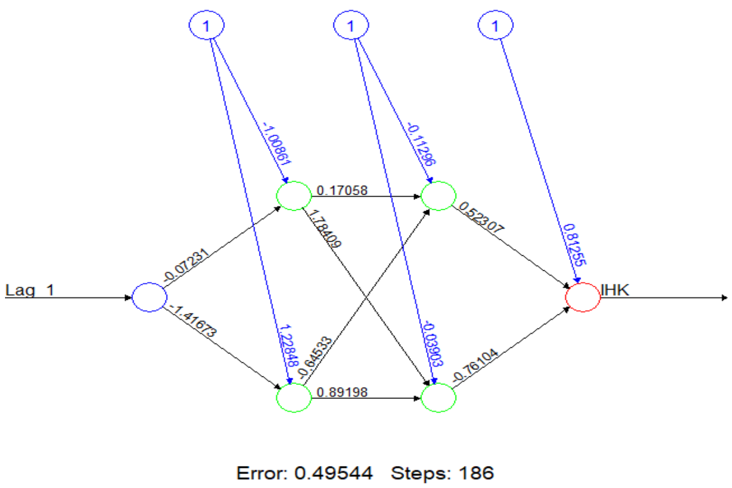

Figure 9. Best Network Architecture

Systematically, the neural network model uses one input layer and two hidden layers containing two nodes as follows:

$$y_k = \sum_{l=1}^{2} w_{kl} \cdot f\left[w_{j0} + \sum_{j=1}^{2} w_{kj} \cdot f\left[v_{j0} + \sum_{i=1}^{2} x_i v_{ji}\right]\right] + w_{k0} \tag{7}$$

The data used to build the neural network model using one input layer and two hidden layers containing two nodes are CPI training data (January 2006-January 2018). The input value for the February 2018 CPI prediction is the previous 1-month CPI data. The CPI value in January 2018 was 132.10. Before making a prediction, the January 2018 CPI data should be normalized to .0.46531501.

The output operation of the jth input to the first hidden layer is as follows:

$$z_{net_j} = v_{j0} + \sum_{i=1}^{2} x_i v_{ji}$$

$$= \begin{bmatrix} -1.008609 \\ 1.228481 \end{bmatrix} + \begin{bmatrix} -0.072311 \\ -1.416731 \end{bmatrix} [0.46531501]$$

$$= \begin{bmatrix} -1.0422564 \\ 0.5692548 \end{bmatrix}$$

Using the Leaky ReLU activation function is obtained

$$z_j = f(z_{net\,j})$$

$$z_j = f(z_{inj}) = \begin{Bmatrix} 0{,}01x\,;x < 0 \\ x\,;x \geq 0 \end{Bmatrix}$$

$$= f\begin{pmatrix} -1.0422564 \\ 0.5692548 \end{pmatrix}$$

$$= \begin{bmatrix} -0{,}010422564 \\ 0.5692548 \end{bmatrix}$$

The output operation of the first hidden layer to the second hidden layer is as follows:

$$q_{net\,j} = w_{j0} + \sum_{j=1}^{2} w_{kj}.z_j$$

$$q_j = f\left(q_{net\,j}\right)$$

$$= f\left(\begin{bmatrix} -0.112957899 \\ -0.039027293 \end{bmatrix} + \left(\begin{bmatrix} 0.170582586 & -0.645326496 \\ 1.784088380 & 0.891977439 \end{bmatrix}\begin{bmatrix} -0{,}010422564 \\ 0.5692548 \end{bmatrix}\right)\right)$$

$$= f\left(\begin{bmatrix} -0.4820910 \\ 0.4501404 \end{bmatrix}\right) = \begin{bmatrix} -0{,}00482091 \\ 0.4501404 \end{bmatrix}$$

Output operation on a hidden layer with additional neurons towards the output layer:

$$y_k = y_{net\,k} = w_{k0} + \sum_{l=1}^{2} w_{kl}.q_j$$

$$= 0.812553906 + \left([0.523065569 \quad -0.761038252]\begin{bmatrix} -0{,}00482091 \\ 0.4501404 \end{bmatrix}\right)$$

$$= 0.4674582$$

$$y_k = 0.4674582$$

The obtained value will then be denormalized to find out the data in the original form. To perform the denormalization process, use the equations:

$$x = [x^*(x_{max} - x_{min})] + x_{min}$$

$$= [0.4674582(164.01 - 104.33)] + 104.33)$$

$$= 132.22$$

In other words, the cpi prediction results in February 2018 amounted to. So the result was predicting the value of CPI in February 2018 using132.22 the backpropagation algorithm, where the actual CPI value is 132.32.

3.9. Consumer Price Index Forecasting Results

After obtaining the GARCH and ANN models for forecasting the value of the CPI, CPI forecasting will be carried out for the next 12 months. Here are the forecasting results with the help of R-Studio software:

Table 11. CPI Forecasting Results

Moon	Forecasting		Original Data
	GARCH	ANN	
January 2021	105.05	106.46	105.95
February 2021	104.73	107.07	106.06
March 2021	104.47	107.55	106.15
April 2021	103.92	107.98	106.29
May 2021	103.78	108.40	106.63
June 2021	103.20	108.69	106.46
July 2021	103.04	108.93	106.54
August 2021	102.52	109.13	106.57
September 2021	102.29	109.30	106.53
October 2021	101.85	109.45	106.66
November 2021	101.55	109.58	107.05
December 2021	101.17	109.70	107.66
January 2022	100.83	109.80	-
February 2022	100.48	109.89	-
March 2022	100.13	109.97	-
April 2022	99.79	110.04	-
May 2022	99.43	110.10	-
June 2022	99.10	110.16	-
July 2022	98.75	110.22	-
August 2022	98.42	110.28	-
September 2022	98.07	110.33	-
October 2022	97.73	110.38	-
November 2022	97.39	110.42	-
December 2022	97.06	110.46	-

3.10. GARCH and ANN Model Evaluation

After obtaining the best model, the accuracy of the model that has been obtained will be seen. In looking at the best model, the author uses mape values because of the reference. Here are the results of MAPE values with the help of R-Studio software:

Table 12. MAPE Value

Model	MAPE value	Accuracy
ARIMA (4, 2, 2)~GARCH(1, 1)	3.19%	96.81%
ANN	1.24%	98.76%

Based on Table 12, it can be seen that the accuracy of the ANN model is better compared to the GARCH model. Thus, the ann network structure can produce a more accurate CPI value forecasting value than the GARCH model.

4. CONCLUSIONS

Model performance obtained using ARIMA model (4, 2, 2) ~ GARCH (1, 1) with a MAPE value of 3.19% and ANN network structure with one input and two best-hidden layers with a MAPE value of 1.24% to forecast the value of the Consumer Price Index (CPI). Meanwhile, the ANN model produces a better forecast accuracy than the GARCH model. The ANN model has a MAPE value of 1.24%, or accuracy of 98.76%, while the ARIMA model (4,2,2)~GARCH(1.1) has a MAPE value of 3.19% or an accuracy of 96.81%. However, the ARIMA model (4, 2, 2) obtained still has an ARCH effect; in other words, there are still symptoms of heteroscedasticity, so it is recommended to use the GARCH model. While data analysis using the ANN method does not need to be done with data assumptions, the data is of good quality, or the data must go through the KDD process to build ANN network structures.

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