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Artificial Neural Network Model for Forecasting Inflation Rate in Indonesia Using Backpropagation Algorithm

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Abstract- Inflation is defined as a general and persistent rise in prices. Stable inflation is a prerequisite for sustainable economic growth. The importance of controlling inflation is based on the consideration that high and unstable inflation hurts the socio-economic conditions of the community. In this context, government and economic agents must know the future inflation rate. The backpropagation algorithm forecasting method can be a mathematical tool to forecast future inflation rates. The best forecasting model is obtained from applying the backpropagation algorithm, namely ANN BP (12,2,1), with a mean square error value of 0.15 and an absolute percentage error value of 11.09%. Based on these results, the back-propagation algorithm in artificial neural networks can accurately forecast the inflation rate. Thus, it is hoped that this research can be used in economic decision-making.

1. Introduction

Inflation is one of the most serious and complex economic challenges not only in Indonesia but also at the global level (Wiranto, 2003). The stability of inflation is an important factor for sustainable economic growth, which in turn provides benefits for improving people's welfare. Inflation is defined as a general and continuous increase in prices. An increase in the price of only one or two goods cannot be called inflation unless the increase is widespread or results in price increases of other goods (Bank Indonesia, 2024).

According to data from the Central Bureau of Statistics, from 2021 to 2023, there was a significant increase in the inflation rate in 2022. In that year, the peak inflation rate reached 5.95%. However, after this increase, the inflation rate started to decline gradually from the beginning to the middle of 2023, although there was a

Slight increase again towards the end of 2023. This situation shows that inflation in Indonesia is still not fully stabilized. Although inflation has decreased in 2023, an increase is still possible. This condition should not be ignored because if not handled properly, inflation can increase significantly, potentially harming the economy and people's welfare. Therefore, the government and businesses need to understand the forecast of future inflation rates. One method that can be used to forecast inflation is through forecasting analysis techniques. By forecasting the value of inflation in Indonesia in the future period, a prediction number will be obtained so that the government or agencies related to the economy can formulate steps to maintain the stability of inflation in Indonesia if the predicted inflation value for the next period shows an increase (Santoso, 2020).

According to Heizer, J., and Render, B. (2011), forecasting is the science of estimating future events. This can be done by projecting historical data into the future with a mathematical model. One of the forecasting methods that is widely used today is Artificial Neural Network (ANN). According to Aprijani and Sufandi (2011), ANN is an artificial representation of the human brain that always tries to stimulate the learning process in the human brain. ANN can recognize activities based on past data. Past data is learned by ANN so that it can make decisions based on data that has never been studied. An algorithm that is often used for prediction in ANN is the backpropagation algorithm.

According to Salsabila et al (2020), the backpropagation algorithm is one of the multilayer ANN methods that work in a supervised manner, so it is widely used for data prediction and classification. The idea of the backpropagation algorithm is that the neural network input is evaluated against the desired output. If the result is not quite as desired, the connections (weights) between the layers are modified, and the process is repeated until a sufficiently small error value is obtained. The application of the backpropagation algorithm for forecasting has been carried out by Syaharuddin (2020), namely forecasting the poverty rate in Indonesia using the backpropagation algorithm. The data used in this study is the annual period of poverty data for 8 years, from 2012 to 2019. This research obtained high accuracy results with a mean square error value of 0.346 and a mean absolute percentage error of 2.298. Another research conducted by Amaly (2022) compares ANN Backpropagation and ARMA methods for forecasting inflation in Indonesia. The results of this study explain that the most optimal method for forecasting inflation in Indonesia for the coming period is ANN Backpropagation with Mean Square Error (MSE) = 0.0112 and Root Mean Square Error (RMSE) = 0.1065. Meanwhile, the ARMA method obtained a mean square error (MSE) = 0.0648 and root mean square error (RMSE) = 0.2545. Based on the previous explanation, this research will apply a forecasting method using Artificial Neural Network (ANN) with the Backpropagation algorithm to predict the future inflation rate. The results obtained are expected to be the basis for forecasting inflation and help determine policies to reduce the negative impact caused by inflation.

2. Methods

The type of data used in this study is secondary data obtained from the website https://www.bi.go.id/. The data used is on Indonesia's inflation rate from January 2014 to December 2024, with 132 observations. The data in this study is a time series that contains variable values based on monthly time intervals and is numerical. The method used in this research is the artificial neural network method based on the back propagation algorithm.

Analyzing an artificial neural network based on the backpropagation algorithm requires several stages (Kusumadewi, 2004).

1. Perform the data normalization process so that the input and output data are in the value range of 0 to 1. The formula used is as follows (Siang, 2005).
$$z = \frac{x_i - x_{min}}{x_{max} - x_{min}}$$
2. Initialize the weights, set the target error, the maximum number of epochs, and the learning rate (α).
3. Performing the Forward Propagation Phase
   a. Each unit in the input layer receives an input signal x_i, where i = 1,2,3, … , n, and then all units in the next hidden layer receive a continuation of the signals. Each unit in the hidden layer, denoted as z_j with j = 1,2,3, … , pSums the weighted input signals.
$$z\_in_j = v_{0j} + \sum_{i=1}^{n} x_i v_{ij}$$

   Description:

z_in_j	The number of input layer neuron signals going to the j-th hidden layer neuron ($j = 1,2,3,\dots,p$)
v_{0j}	: the weight connecting the input layer bias neuron with the j-th hidden layer neuron ($j = 1,2,3,\dots,p$)
v_{ij}	: the weight connecting the i-th neuron of the input layer ($i = 1,2,3,\dots,i$) to the j-th neuron of the hidden layer ($j = 1,2,3,\dots,p$)

x_i : the value of the i-th neuron of the input layer ($i = 1,2,3,\dots,i$)

n Number of neurons in the input layer

The activation function is then used to calculate the output value.

$$z_j = f(z\_in_j) = \frac{1}{1 + e^{-z\_in_j}}$$

b. Then, the output layer sends a signal to all units. Each unit in the output layer, which is marked as y_k where $k = 1,2,3,\dots,m$The input signal from each layer will be summed with the weight.

$$y_{ink} = w_{0k} + \sum_{j=1}^{p} z_j w_{jk}$$

Description:

y_in_k	: the number of hidden layer neuron signals going to the k-th output layer neuron ($k = 1,2,3,\dots,m$)
w_{0k}	The weight connecting the hidden layer bias neuron with the output layer neuron ($k = 1,2,3,\dots,m$)
w_{jk}	: the weight connecting the j-th hidden layer neuron ($j = 1,2,3,\dots,p$) to the k-th output layer neuron ($k = 1,2,3,\dots,m$)
z_j	value of the j-th hidden layer neuron ($j = 1,2,3,\dots,p$)
p	number of hidden layer neurons

Next, the output value is calculated using the activation function.

$$y_k = f(y_{ink}) = \frac{1}{1 + e^{-y\_in_k}}$$

4. Performing the Backpropagation Phase
   a. Each output unit y_k, where $k = 1,2,3,\dots,m$Receives a target (expected output) compared to the resulting output.

$$\delta_k = (t_k - y_k) f'(y_{ink})$$

Description:

δ_k	Value of the error factor at the k-th output layer neuron
t_k	Value of the actual data at the t-th time
y_k	Value of the output layer at the t-th time
y_in_k	The number of hidden layer neuron signals entering the k-th output layer neuron ($k = 1,2,3,\dots,m$).

This δ_k The Factor is used to calculate the error correction (Δw_{jk}) which will be used to update w_{jk}, where:

$$\Delta w_{jk} = \alpha \delta_k z_j$$

Description:

Δw_{jk}	Weight correction between the j-th hidden and k-th output layer neurons.
α	learning rate coefficient
δ_k	error factor value of the k-th output layer neuron
z_j	value of the j-th hidden layer neuron ($j = 1,2,3,\dots,p$)

It also calculates the bias correction Δw_{0k} used to update w_{0k}, where:

$$\Delta w_{0k} = \alpha \delta_k$$

Description:

Δw_{0k}	Bias weight correction between the j-th hidden and k-th output layer neurons.
α	learning rate coefficient

δ_k error factor value at the k-th output layer neuron

This δ_k The factor is then sent to the layer above.

b. For each hidden unit z_j where j = 1,2,3,…, pThe units in the hidden layer are summed to obtain the delta input:

$$\delta_{inj} = \sum_{k=1}^{m} \delta_k w_{jk}$$

Description:

δ_in$_j$ Number of error factors in the j-th hidden layer neuron

δ_k : Error factor value at the k-th output layer neuron

w_{jk} : Weights connecting the j-th hidden layer neuron (j = 1,2,3,…, p) to the k-th output layer neuron (k=1,2,3,...,m).

The result is then multiplied by the derivative of the activation function used by the network to produce the error correction factor δ_j, where

$$\delta_j = \delta_{inj} f'(z_{inj})$$

Description:

δ_j : value of the error factor in the j-th hidden layer neuron

δ_in_j : number of error factors in the j-th hidden layer neuron

z_in_j : number of input layer neuron signals entering the j-th hidden layer neuron ($j = 1,2,3,\dots,p$)

This δ_j factor is used to compute the error correction (Δv_{ij}) used to update v_{ij}, where

$$\Delta v_{ij} = \alpha \delta_j x_i$$

Description:

Δv_{ij} : Weight correction between the i-th hidden layer neuron and the j-th hidden layer neuron.

α : learning rate coefficient

δ_j : error factor value in the j-th hidden layer neuron

x_i : value of the i-th input layer neuron ($i = 1,2,3,\dots,n$)

It also calculates the bias correction. Δv_{0j} used to update v_{0j}, where:

$$\Delta v_{0j} = \alpha \delta_j$$

Description:

Δv_{0j} : Bias weight correction between the i-th hidden layer neuron and the j-th hidden layer neuron.

α : learning rate coefficient

δ_j : error factor value for the j-th hidden layer neuron

5. Performing the Weight Change Phase

a. Each output unit y_k where k = 1,2,3,…, m, will experience an update of the bias value along with the weight value (with $j = 1,2,3,\dots,p$):

$$w_{jk}(new) = w_{jk}(old) + \Delta w_{jk}$$
$$w_{0k}(new) = w_{0k}(old) + \Delta w_{0k}$$

b. Each hidden unit z_j (where $j = 1,2,3,\dots,p$) will also have its bias and weight (where $i = 1,2,3,\dots,n$) updated:

$$v_{ij}(new) = v_{ij}(old) + \Delta v_{ij}$$
$$v_{0j}(new) = v_{0j}(old) + \Delta v_{0j}$$

Description:

$w_{jk}(new)$: the new weight value connecting the j-th hidden layer neuron to the k-th output layer neuron

$w_{jk}(old)$: the old weight value connecting the j-th hidden layer neuron to the k-th output layer neuron

$w_{0k}(new)$: the value of the new bias weight at the k-th output layer

$w_{0k}(old)$: the old bias weight value at the k-th output layer $v_{ij}(new)$: the new weight value connecting the i-th neuron of the input layer with the j-th neuron of the hidden layer

$v_{ij}(old)$: the old weight value connecting the i-th neuron of the input layer with the j-th neuron of the hidden layer

$v_{0j}(new)$: the value of the new bias weight at the j-th hidden layer

$v_{0j}(old)$: the value of the old bias weight at the j-th hidden layer

6. Check the stopping condition. When the stopping condition is met, the network training can be stopped. There are two common ways to determine the stopping condition, namely
   a. Limit the number of iterations to be performed.
      a) Suppose the network is trained to the 500th iteration.
      b) An iteration repeats steps 3 through 5 for all available training data.
   b. Limiting errors
      For example, determine the mean square error between the desired output and the output produced by the network.

3. Results and Discussion

Before analyzing inflation rate data, it is necessary to explore the data first. Data exploration is done to see the characteristics or overview of inflation data from January 2014 to December 2024. The exploration of inflation data in the period from January 2014 to December 2024, in general, can be seen in Table 1.

Table 1. Exploration of inflation rate variables is able

Variable	N	Mean	Minimum	Maximum
Inflation rate	132	3.786	1.32	8.36

Table 1 shows that the data used consists of only one variable, the inflation rate data. The inflation rate data consists of 132 observations, with the lowest inflation rate at 1.32 and the highest at 8.36.

Before the data analysis process, the data normalization process is performed. One purpose of normalization is to make the data used stable, as data with a wide range of values can cause instability in the numerical calculations in the model. The inflation data from January 2014 to December 2024 are normalized so that they are in the interval from 0 to 1. Table 2 shows the results after the data normalization process.

Table 2. Normalized data of the inflation rate in Indonesia for the period January 2021 - December 2023

Tahun	Bulan ke-											
	1	2	3	4	5	6	7	8	9	10	11	12
2014	0.98	0.91	0.85	0.84	0.85	0.76	0.46	0.38	0.46	0.5	0.7	1
2015	0.8	0.71	0.72	0.78	0.83	0.84	0.84	0.83	0.78	0.7	0.51	0.29
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
2023	0.56	0.59	0.52	0.43	0.38	0.31	0.25	0.28	0.14	0.18	0.22	0.18
2024	0.18	0.2	0.25	0.24	0.22	0.17	0.12	0.11	0.07	0.06	0.03	0.04

After the normalization process is performed and the results are obtained as in Table 2, the normalized inflation rate data are modified using the windowing method, and the results are obtained as modified data in Table 3.

Table 3. Modified Windowing Inflation Rate Data

Pattern	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Target
1	0.9801	0.9134	0.8523	0.8423	0.8523	0.7642	0.4560	0.3793	0.4560	0.4986	0.6974	1.0000	0.9495
2	0.9134	0.8523	0.8423	0.8523	0.7642	0.4560	0.3793	0.4560	0.4986	0.6974	1.0000	0.8011	0.8367
3	0.8523	0.8423	0.8523	0.7642	0.4560	0.3793	0.4560	0.4986	0.6974	1.0000	0.8011	0.7060	0.8519
4	0.8423	0.8523	0.7642	0.4560	0.3793	0.4560	0.4986	0.6974	1.0000	0.8011	0.7060	0.7188	0.9209

⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
119	0.2188	0.1832	0.1776	0.2031	0.2457	0.2386	0.2159	0.1690	0.1151	0.1136	0.0739	0.0554	0.0387
120	0.1832	0.1776	0.2031	0.2457	0.2386	0.2159	0.1690	0.1151	0.1136	0.0739	0.0554	0.0327	0.0421

After obtaining data with the structure shown in Table 3, the next step is to divide the data into two parts, namely 80% training data and 20% test data (Adeyinka & Muhajarine, 2020). Thus, patterns 1 to 96 are used as training data, while patterns 97 to 120 are used as test data. In performing the backpropagation algorithm, 3 networks are formed: the input, hidden, and output layers. The data used as the input layer are variables from X1 to X12. Meanwhile, the number of hidden layers used is unlimited because there is no standard rule regarding this number. A hidden layer with 2 to 12 neurons is used in this case.

Next, the best ANN model is determined through a trial-and-error process. The trial-and-error process is performed because the number of neurons in the hidden layer affects the level of accuracy produced. The best ANN model is selected based on the lowest MSE and MAPE values of the trial-and-error process. However, the training process is performed before testing so that the model learns to adjust the weights and biases to minimize errors. Table 4 shows the network model formed by the ANN method based on the backpropagation algorithm on the training data.

Table 4. Best model of training data

Model ANN	Neuron Hidden	MSE	MAPE
ANN BP(12,2,1)	2	0.2	10.61%
ANN BP(12,3,1)	3	0.24	14.25%
ANN BP(12,4,1)	4	0.22	11.59%
ANN BP(12,5,1)	5	0.22	12.13%
ANN BP(12,6,1)	6	2.47	43.15%
ANN BP(12,7,1)	7	0.24	11.54%
ANN BP(12,8,1)	8	2.32	41.67%
ANN BP(12,9,1)	9	2.37	42.16%
ANN BP(12,10,1)*	**10**	**0.18**	**10.21%**
ANN BP(12,11,1)	11	2.46	43.08%
ANN BP(12,12,1)	12	0.23	11.21%

***Model Terbaik**

Based on Table 4, 11 possible ANN models can be used to forecast the inflation rate in Indonesia. However, among the 11 models that meet the MSE and MAPE criteria, the smallest model is the BP (12,10,1) ANN model with MSE 0.18 and MAPE 10.21%. Table 4 also shows that adding neurons in the hidden layer does not guarantee that the ANN model formed will be better; this happens because adding neurons in the hidden layer does not make the MSE and MAPE values smaller. Next, the models are tested on test data to see which model to use. The results of the model tests on the test data are shown in Table 5.

Table 5. Best model of test data

Model ANN	Neuron Hidden	MSE	MAPE
ANN BP(12,2,1)*	**2**	**0.15**	**11.09%**
ANN BP(12,3,1)	3	0.21	12.90%
ANN BP(12,4,1)	4	0.15	11.59%
ANN BP(12,5,1)	5	0.24	12.34%
Model ANN	Neuron Hidden	MSE	MAPE
ANN BP(12,6,1)	6	1.56	35.72%
ANN BP(12,7,1)	7	0.18	12.69%
ANN BP(12,8,1)	8	1.47	34.58%
ANN BP(12,9,1)	9	1.5	35%
ANN BP(12,10,1)	10	0.15	12.30%

ANN BP(12,11,1)	11	1.56	35.62%
ANN BP(12,12,1)	12	0.2	12.77%

***Model Terbaik**

In the test data, the best model produced is the ANN BP (12,2,1) model with an MSE value of 0.15 and an MAPE value of 11.09%. The results of the MSE and MAPE values explain that the model is good enough to perform the prediction process with an error rate of 11.09%. Based on the results in Tables 4 and 5, it can also be concluded that the best models on the training data and the test data are unrelated, because the best models on the two datasets are different. Figure 1 explains the comparison graph between test and actual data using the ANN BP (12,2,1) model.

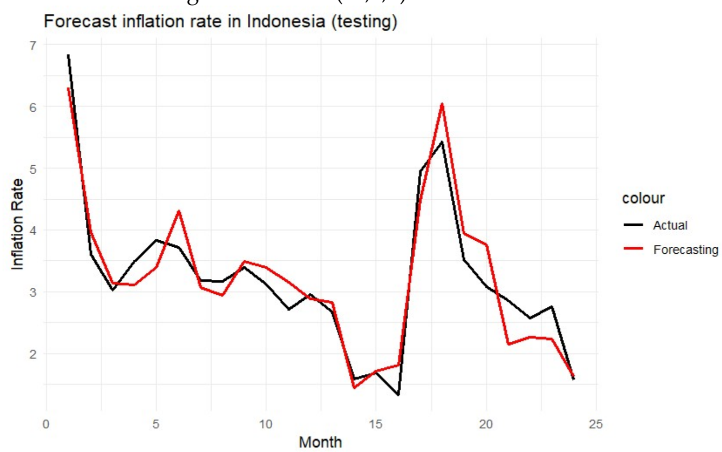

Figure 1. Comparison chart of test data prediction results and actual data

Based on Figure 1, it can be seen that the ANN BP (12,2,1) model shows excellent performance in predicting the test data. This is indicated by the line of prediction results, which are very close to and follow the trend pattern of the actual data, both in the fluctuation and the direction of movement of the inflation rate. Although there is a slight deviation at some points, the model can generalize to new data. This closeness between the forecast data and the actual data indicates that the model can accurately capture historical patterns and has a high generalization ability to data that has never been trained.

These results are consistent with those of a study conducted by Syaruddin (2020), who predicted the poverty rate in Indonesia using the backpropagation algorithm. The study showed a high level of accuracy, with a Mean Square Error (MSE) value of 0.346 and a Mean Absolute Percentage Error (MAPE) value of 2.298, reinforcing the backpropagation algorithm's effectiveness in forecasting. The consistency of these results indicates that the backpropagation algorithm has great potential in various time series forecasting contexts.

Furthermore, the results of this study are also supported by the findings of Amaly (2022), who used the ANN backpropagation method to forecast Indonesia's inflation rate. In his research, Amaly compared the ANN backpropagation method with ARMA, and the results showed that ANN backpropagation was more optimal with a Mean Square Error (MSE) value of 0.0112 and a Root Mean Square Error (RMSE) of 0.1065. Meanwhile, the ARMA method produces a higher MSE of 0.0648 and an RMSE of 0.2545. Although the MSE value in this study is higher (0.15), the difference may be due to differences in the amount of data, network structure, and input variables used. Nevertheless, these three studies consistently show that ANN backpropagation is an effective and superior method in forecasting inflation in Indonesia, while strengthening the relevance and validity of using the ANN BP (12,2,1) model in economic forecasting.

4. Conclusion

Based on the results of the research and discussion that have been done, 11 Artificial Neural Network models with Backpropagation Algorithm (ANN BP) are obtained to forecast the inflation rate in Indonesia. Of all these models, the best model is obtained with the ANN BP architecture (12,2,1). The selection of this model is based on the lowest values of Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE), which indicates that the model has the highest level of accuracy compared to other models. Therefore, the ANN BP (12,2,1) model is considered very effective in forecasting the

inflation rate in Indonesia. The results of this study are expected to be a reference in forecasting inflation in the future, and can be used as a tool in decision-making in the economic field. In addition, this research is also expected to contribute as a reference for future studies that raise similar issues.
This study used 132 data points, which is still relatively limited. Therefore, it is recommended that future studies use a larger amount of data to increase the model's generalizability. In addition, this study was constrained by the relatively long model training time. To overcome this, it is recommended to use accelerated training techniques such as adding momentum coefficients or other optimization methods to improve the efficiency of the network learning process.

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