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Modeling Multi-Output Back-Propagation DNN for Forecasting Indonesian Export-Import

Rengganis Woro Maharsi[1*], Wisnowan Hendy Saputra[2], Nila Ayu Nur Roosyidah[3], Dedy Dwi Prastyo[4], Santi Puteri Rahayu[5]

[1]BPS- Statistics Indonesia, Tanggamus Regency, Lampung, [2,4,5]Departement of Statistics, Institut Teknologi Sepuluh Nopember, Surabaya 60111, Indonesia, [2]BPS-Statistics Indonesia, Poso Regency, Central Sulawesi
**Corresponding Author: E-mail address: [1]rengganis@bps.go.id, [2]wisnowanwhs@gmail.com, [3]nila.roosyidah@bps.go.id*

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Abstract

Introduction/Main Objectives: International trade through the mechanisms of exports and imports plays a significant role in the Indonesian economy, making the timely availability of export and import value data crucial. **Background Problems:** Export and import values are influenced by inflation and exchange rate factors. **Novelty:** This study identifies two categories of variables, namely output (export value and import value) and input (inflation rate and the exchange rate of the Rupiah against the US Dollar). **Research Methods:** the research approach utilizes a Multi-output Deep Neural Network (DNN) with a Back-propagation algorithm to model the input-output relationship. The method can provide forecasting results for two or more bivariate or multivariate output variables. **Finding/Results:** The modeling analysis results indicate that the optimal model network structure is DNN (3.4). This model successfully predicts output 1 (export value) and output 2 (import value) with Mean Absolute Percentage Error (MAPE) rates of 13.76% and 13.63%, respectively. Additionally, the forecasting results show predicted export and import values for November to be US$ 16,208.13 billion and US$ 15,105.33 billion, respectively. These findings offer important insights into the direction of Indonesia's international trade movement, which can serve as a basis for future economic decision-making.

1. Introduction

Globalization economy resulted in a significant increase in international trade activity, particularly in the value of exports and imports. The growth in the value of exports and imports, which was triggered by rising commodity prices and recovering global demand, is a major concern for export and import industry players. In Indonesia, the impressive performance of the trade balance has succeeded in keeping the current account deficit low, namely below 1 percent of Gross Domestic Product (GDP) in 2020 and Semester I-2021 [1].

The increase in Indonesian exports to the international market has encouraged growth in the domestic production of goods and services, which indicates the need for greater production input factors, including labor. This phenomenon also triggers an increase in demand for labor, which in turn leads to full employment and efficiency in economic growth.

In the context of imports, research by Rofiyandi [2] shows that the right imports can provide high efficiency in the production process by providing raw materials at cheaper prices and sophisticated industrial equipment that can increase output. However, it is important to remember that excessive imports, especially of consumer goods, can hurt the economy and cause a balance of payments deficit.

International trade is a key element in supporting a country's economy, with accurate and timely data regarding exports and imports being the key for the government to formulate appropriate fiscal and monetary policies [3]. Therefore, developing a prediction model that can predict these two components accurately at run time, based on relevant indicators, is important (Forecasting).

In the context of the influence of external factors, such as currency exchange rates and inflation [4], on exports and imports, previous research shows that changes in currency exchange rates can directly influence domestic prices of goods and services, with a significant impact on the volume of exports and imports. Likewise with inflation, which can affect exports and imports simultaneously by causing an increase in the prices of goods and services, which ultimately has an impact on the volume of international trade.

In dealing with the complexity of export and import data, as well as the limitations of classical assumptions in regression analysis, the use of Machine Learning methods, especially Multi-output Back-propagation DNN [5], becomes relevant. This method was chosen because of its ability to predict data at a running time based on independent variable information, without having to rely on certain assumptions which are often difficult to fulfill in an economic context.Thus, this research attempts to fill the gap in the literature by exploring the potential of Machine Learning methods in predicting the value of Indonesian exports and imports.

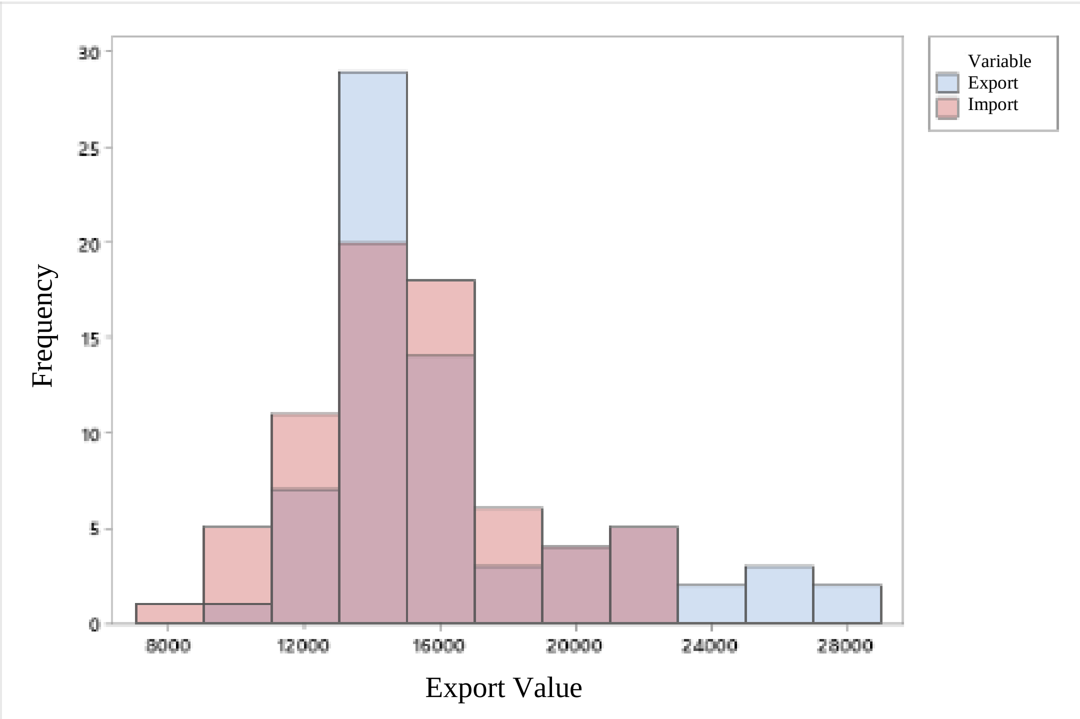

Figure. 1. Histogram of Indonesian Export and Import Values, January 2017 to October 2022

2. Material and Methods

2.1. Model Prediction

The modeling introduced to overcome prediction problems is mostly a linear model. The linear model has absolute requirements that must be met, namely the existence of a linear relationship. Most methods are only designed to solve problems in the case of linear predictions.

Some real cases certainly cannot demand certain conditions from the resulting data and are relatively freer. Therefore, in some cases, non-linear conditions are often found. Most of the literature directs the decomposition method to separate linear and non-linear aspects so that they can be analyzed separately.

Most of the time series data in various cases are non-linear conditions. The decomposition process is considered to be able to reduce or even eliminate important information from non-linear time series data. Yokota et al. [6] suggested using non-linear methods to overcome problems in these conditions. Apart from that, Levenberg [7] confirmed that non-linear methods were developed to solve problems in non-linear cases.

As time goes by, many modern methods have emerged that focus on non-linear conditions [8]. The Machine Learning (ML) method is a non-linear modeling method that utilizes computational capabilities as an optimization tool [9]. Artificial Neural Network (ANN) or Neural Network (NN) is an ML that is adapted from the functioning of nerves in humans. NN was first introduced by McCulloch and Pitts in 1943 [10]. The idea of this method is to predict output values based on several input values that have been given from several observations. In the case of time series, observations can be interpreted as a time sequence with a certain length.

In general, many types of NN methods are developed according to the objectives and background of the existing problem [11-12-13]. The Deep Neural Network (DNN) method was developed to obtain accurate output predictions with increasingly complex computational algorithms. Apart from that, Mishra and Passos [14] explained that ordinary NNs cannot be used in multivariate cases and explained that there is a need to develop Multi-output NNs.

Modeling that is focused on predicting time series data certainly requires evaluation. The Mean Absolute Percentage Error (MAPE) is the best performance measure used on non-negative time series data. MAPE has a clearer range of values and interpretation boundaries.

2.2. Linearity

The theory of linearity in time series data explains that time series data can be approximated by a straight line or has a relatively straight pattern. In some cases, especially for time series data, linear conditions are very difficult to recognize. Therefore, many tests have been developed which are used to validate the linear condition of data.

Teräsvirta [15] is one of the researchers who developed the linearity test. This test was first introduced in 1994 and was then called the Terasvirta test [15]. The idea of the Terasvirta test was specifically adapted based on the NN model. According to Prabowo et al. [16], the Terasvirta test is the most accurate linearity test because it has the highest sensitivity based on other tests.

2.3. Artificial Neural Network

Artificial Neural Network (ANN) is a science developed by Warren McCulloch and Walter Pitts in 1943 [17]. ANN is an information processing pattern initiated by the biological nervous system, such as information processing in the human brain. The essence of this idea is the structure contained in information processing systems which consists of interconnected process elements (neurons) that then work simultaneously to solve certain problems.

Not far from the human network, the ANN structure consists of an input layer, a hidden layer, and an output layer. Information (α) will be received by the input layer using a certain arrival weight (w). After that, the weights will be added to the hidden layer. Then the results of the sum will be compared with the threshold value. If the value passes the threshold, it will be passed to the output layer, whereas if the value does not pass the threshold, it will not be passed to the output layer. So that maximum output is obtained. The following is the network structure of ANN.

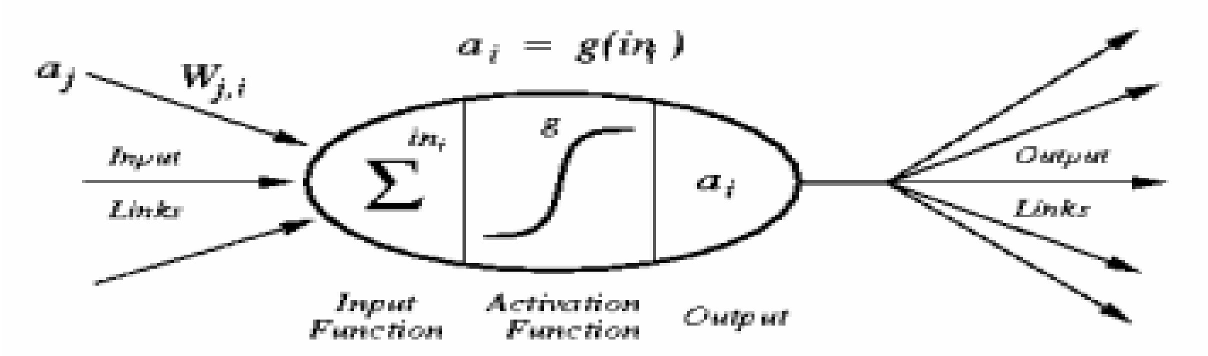

Figure. 2. Structure Network on ANN

The weights in the ANN are estimated using several one of these algorithms is Back-propagation. This algorithm was first introduced by Paul Werbos in 1974 [17]. This algorithm allows repeated weight estimation based on the weights that have been obtained up to a certain error threshold or a certain number of iterations.

2.4. Deep Neural Network

Deep Neural Network (DNN) is a development of the ANN method which involves a large number of hidden layers. In 2011, Deep NN began combining convolutional layers with max-pooling layers whose output was then passed to several fully connected layers followed by an output layer. This condition is called Convolutional Neural Networks (CNN) [17]. In general, estimation process weights in DNN are relatively the same as ANN, but with more time long as well as complexity more computing complicated. Following is one of the form structure networks on DNN.

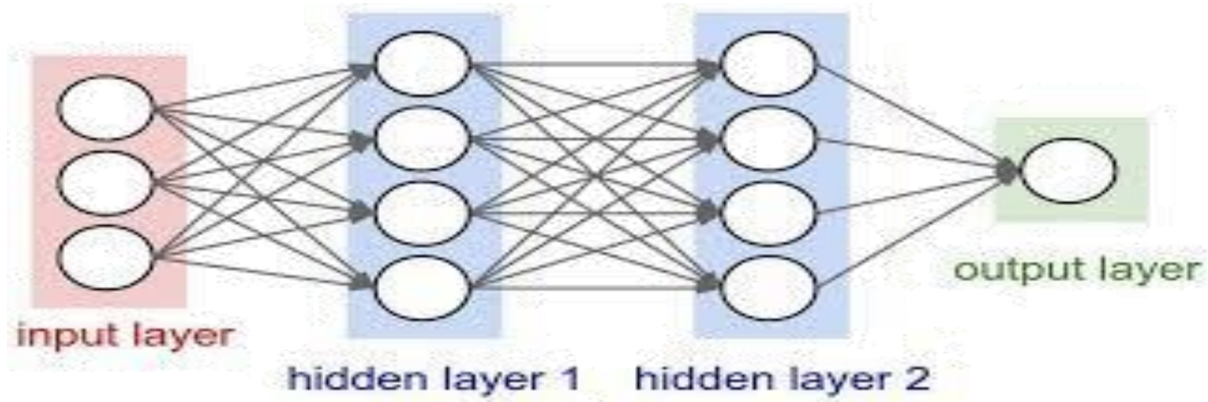

Figure. 3. One form of DNN network structure

2.5. Multi-output Neural Network

ANN is generally used for modeling data with output as much One. Multi-output NN is the development of the ANN used specifically on the type of multivariate model, meaning own total output more from One. As well as with the method Multivariate Ordinary, the output of the NN is modeled in a way direct (multivariate) to predict each value its output based on the input entered. The following is one form of Multi-output NN network structure.

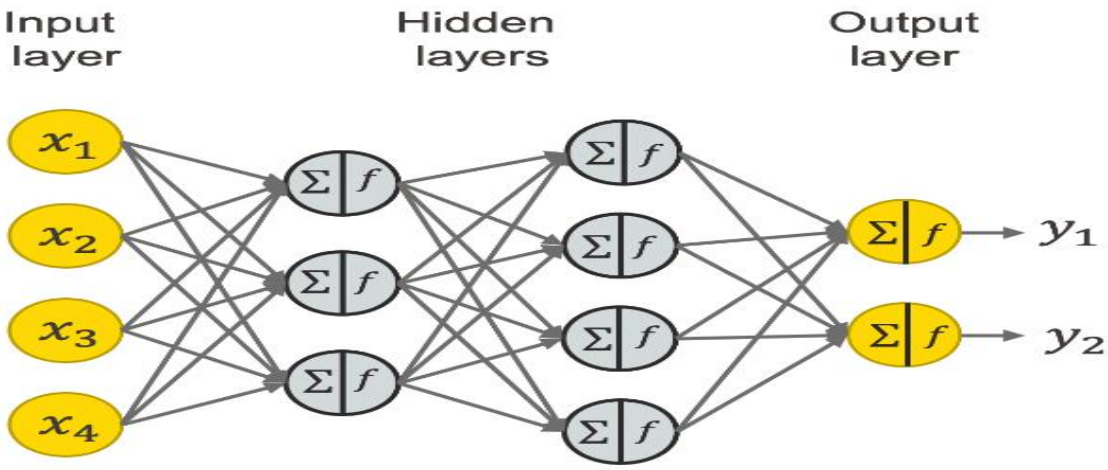

Figure. 4. One form of *multi-output* NN network structure

2.6. Prediction Performance Measures

Evaluating the performance of the time series data modeling method is carried out based on error calculations from the actual data. A prediction performance measure using Mean Absolute Percentage Error (MAPE). Counting level error based on MAPE following a formula like the following.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t-\hat{Y}_t}{Y_t}\right| \times 100\% \tag{1}$$

where Y_t is the actual data, $\widehat{Y_t}$ is the length of the data

Variations of MAPE values have different meanings. If the MAPE value is smaller than 10% then the predictive model's ability is very good [14]. If the MAPE value is between 10% - 20% then the prediction model's ability is good. If the MAPE value is in the range of 20% - 50% then the prediction model's ability is feasible. If the MAPE value ranges more than 50% then the forecasting ability of the model is poor.

2.7. Analysis Method

This research uses secondary data obtained from the Statistics Indonesia (BPS) and Yahoo Finance. The variables used in this research are divided into 2 categories, namely output which consists of export value (Y_1) and import value (Y_2), and input which consists of inflation (X_1) and the Rupiah exchange rate against the United States Dollar (X_2).

Variables of export value, import value, and inflation obtained from BPS accessed through www.bps.go.id. Meanwhile, exchange rate data is obtained via the Yahoo Finance website with the recorded exchange rate being the value in the closing period. The data in this study is monthly data. The research period starts from January 2017 to October 2022, so the number of observations is 70.

Table 1 below is the form of the data structure in this research.

Table 1. Research Data Structure

Month (t)	$Y_{1,t}$	$Y_{2,t}$	$X_{1,t}$	$X_{2,t}$
1	$Y_{1,1}$	$Y_{2,1}$	$X_{1,1}$	$X_{2,1}$
2	$Y_{1,2}$	$Y_{2,2}$	$X_{1,2}$	$X_{2,2}$
⋮	⋮	⋮	⋮	⋮
70	$Y_{1,70}$	$Y_{2,70}$	$X_{1,70}$	$X_{2,70}$

Data was analyzed computationally using the R language with the general stages stated in the following flowchart:

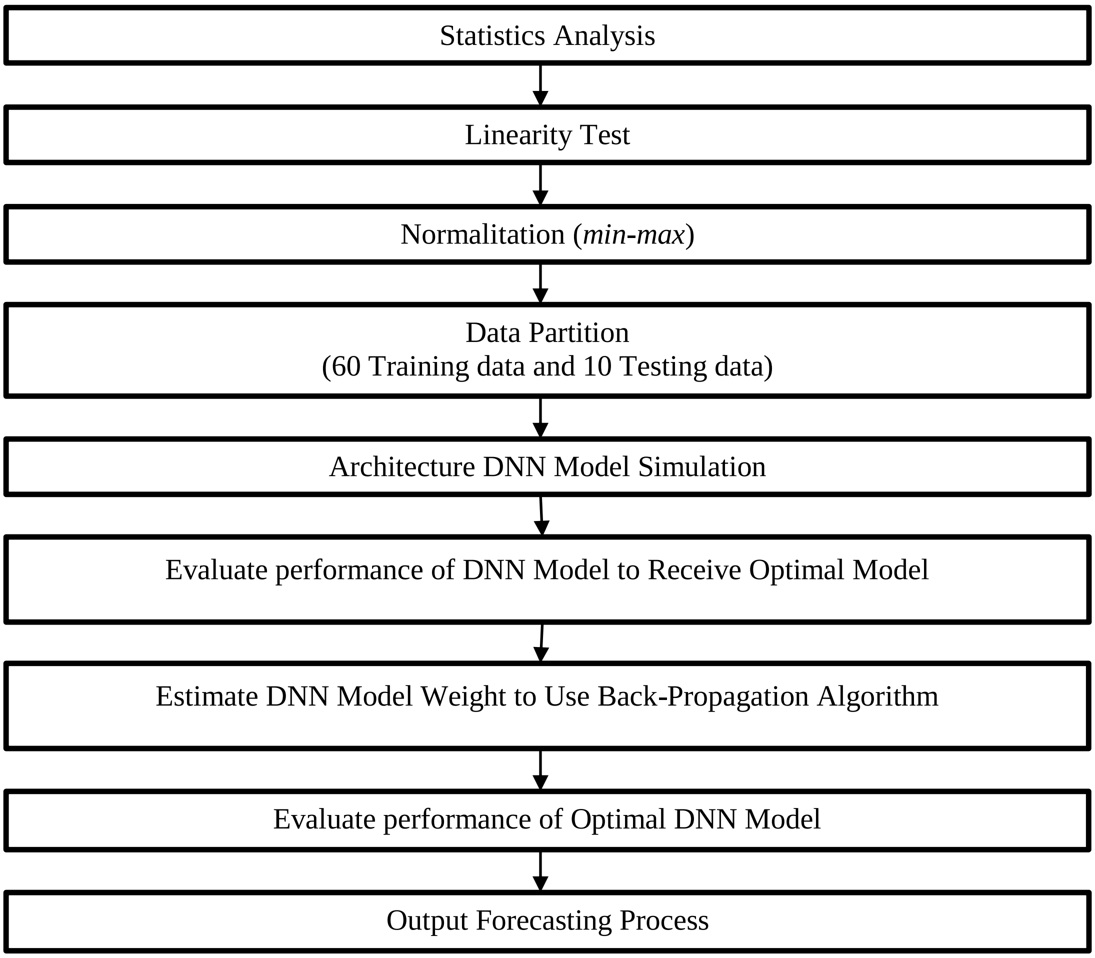

Figure. 5. *Flowchart of* general research stages.

3. Result and Discussion

3.1. Statistics Descriptive

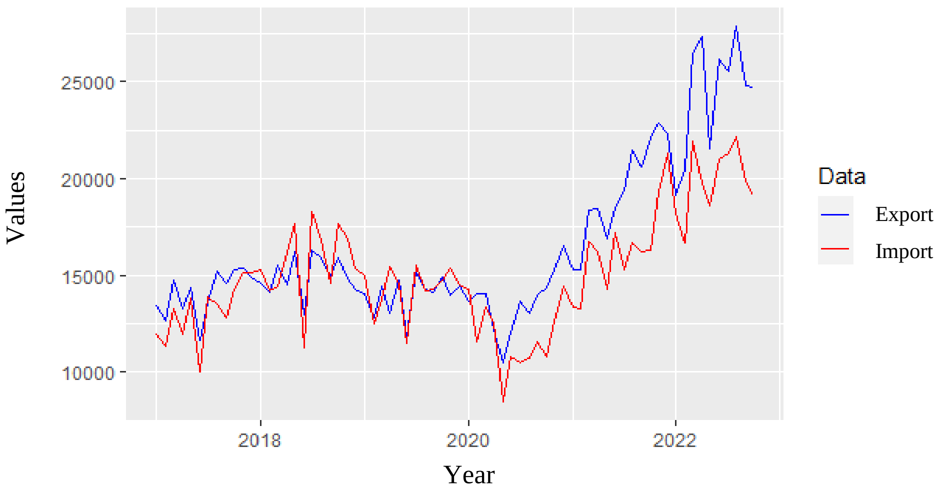

Figure. 6. Development of Indonesian Export and Import Values, January 2017 to October 2022

In general, the development of Indonesia's export and import values, as shown in Figure 5, has almost the same pattern. The majority of Indonesia's imports are capital goods as well as raw materials and industrial auxiliary materials [18]. Capital goods (capital) act as input factors together with other production factors, such as labor (labor) and natural resource factors (land) as raw materials and intermediate materials.

Some raw materials and industrial auxiliary materials cannot be obtained domestically, so imports are required. Apart from that, capital goods also play an important role in building facilities and infrastructure to support industrial activities, such as the construction of transportation infrastructure which supports mobility and distribution of output. Because optimizing input factors in the production process is closely related to the amount of output obtained, the increase in imports is correlated or in line with the increase in exports in Indonesia.

Judging from the movement, Figure 1 shows that both export and import values showed a pattern that tended to be constant from January 2017 to December 2019, then experienced the lowest decline during the research period, starting from January to March 2020 due to the impact of the spread of Covid-19 virus infections. which influences the continuity of production of goods and services in several business sectors in the world. However, starting from April 2020 the movement of both tended to increase even though they experienced a decline several times. The value of exports exceeded the value of imports until the end of the research period, which indicates that during that period the foreign trade balance experienced a surplus.

3.2. Linearity Test

Based on Figure 4, it can be seen that the export and import data relatively have a non-linear pattern. Based on this information, it is of course suspected that the relationship between input and output is not linear. To validate this assumption, a linearity test was carried out using the Terasvirta test. The test was carried out with the following hypothesis.

H_0: Data has a linear relationship

H_1: The data does not have a linear relationship

The results of the tests that have been carried out are obtained according to Table 2. as follows.

Table 2. Terasvirta Test Results

Inputs	Outputs	P-value
X_1 And X_2	Y_1	0.01210
	Y_2	0.05667

Based on Table 2, it is obtained information that with the level significance of the first 5% of output own non-linear relationship with the input used. However, for second output can conclude a relatively linear relationship with the input used. Since there are outputs that have nonlinear relationships, then the condition that machine learning modeling will be better if used than a linear model has been valid.

3.3. Simulation Structure Network

The process of simulating the structure of the network is carried out to obtain a combination of the number of neurons for each hidden layer that is optimal using normalized training data. The amount of hidden layer used is 2 with the putative optimal neuron amount starting from 2 to 4 (twice the number of inputs).

The simulation results obtained are presented in Table 3.

Table 3. Simulation Results Structure Network

Hidden 1	Hidden 2	MAPE Y_1	MAPE Y_2	Number of MAPE
3	4	0.1028	0.1275	0.2303*
2	2	0.1031	0.1274	0.2304
2	4	0.1025	0.1280	0.2306
3	2	0.1036	0.1329	0.2365
3	3	0.1037	0.1330	0.2367
2	3	0.1023	0.1361	0.2383
4	4	0.1041	0.1347	0.2388
4	3	0.1035	0.1357	0.2392
4	2	0.1046	0.1361	0.2407

Table 3 provides information that the most optimal NN network structure based on the MAPE value is NN(3,4). This network structure can predict normalized values Y_1 with an error rate of 0.1028% and normalized values Y_2 with an error rate of 0.1275%. Based on this error level, we can infer that the model has a very excellent prediction capacity for the actual output normalized value.

3.4. *Model Performance Comparison*

The model performance comparison is intended to see the model performance on both data compositions, namely training and testing. The performance results on the training data obtained the same value as the previous stage. The following are the results of the model performance comparison presented in Table 4.

Table 4. Model Performance Comparison

Data	MAPE(Y_1)	MAPE(Y_2)
Training	0.1028	0.1275
Testing	19.0417	13.1136

Based on Table 4, it can be seen that the MAPE in the testing data is very different from the training data. This is due to the limited amount of research data used for testing data. However, this large MAPE value is still considered good because it is below 20%. Thus, it can be concluded that the NN structure has the ability to predict the normalization of outputs on training and testing data well.

3.5. *Final Model Neuron Weight Estimation*

After obtaining the most optimal network structure, this structure is then applied to all data (training + testing) and then the weights are estimated for each neuron. The estimation was carried out based on the NN(3,4) architecture with the Back-propagation algorithm with a maximum number of interactions determined to be 1 million times. The weight estimation results obtained are presented in Table 5., Table 6., and Table 7. sequentially for hidden layer 1, hidden layer 2, and the following output layers.

Table 5. Weights in Hidden Layer 1

	Neuron 1	Neuron 2	Neuron 3
Biased	1.602	0.736	0.886
X_1	-1.036	8.553	7.070
X_2	-5.034	-4.871	-2.309

Table 6. Weights in Hidden Layer 2

	Neuron 1	Neuron 2	Neuron 3	Neuron 4
Biased	1.487	1.633	-2.354	1.072
N_1	2.567	-3.861	-0.235	1.631
N_2	2.144	2.559	0.194	0.835
N_3	-3.528	-4.053	0.465	1.242

Table 7. Weights in the Output Layer

	Y_1	Y_2
Biased	-1.231	-1.265
N_1	3.101	2.623
N_2	4.265	3.581
N_3	-0.702	0.969
N_4	-1.546	-1.089

* N_i: neuron *output* in *hidden layer 1*

Estimating the neuron weights of the final model according to Table 5., Table 6., and Table 7. requires 704201 iterations to reach convergence. Thus, the form of the final model network structure obtained is illustrated in Figure 6 below.

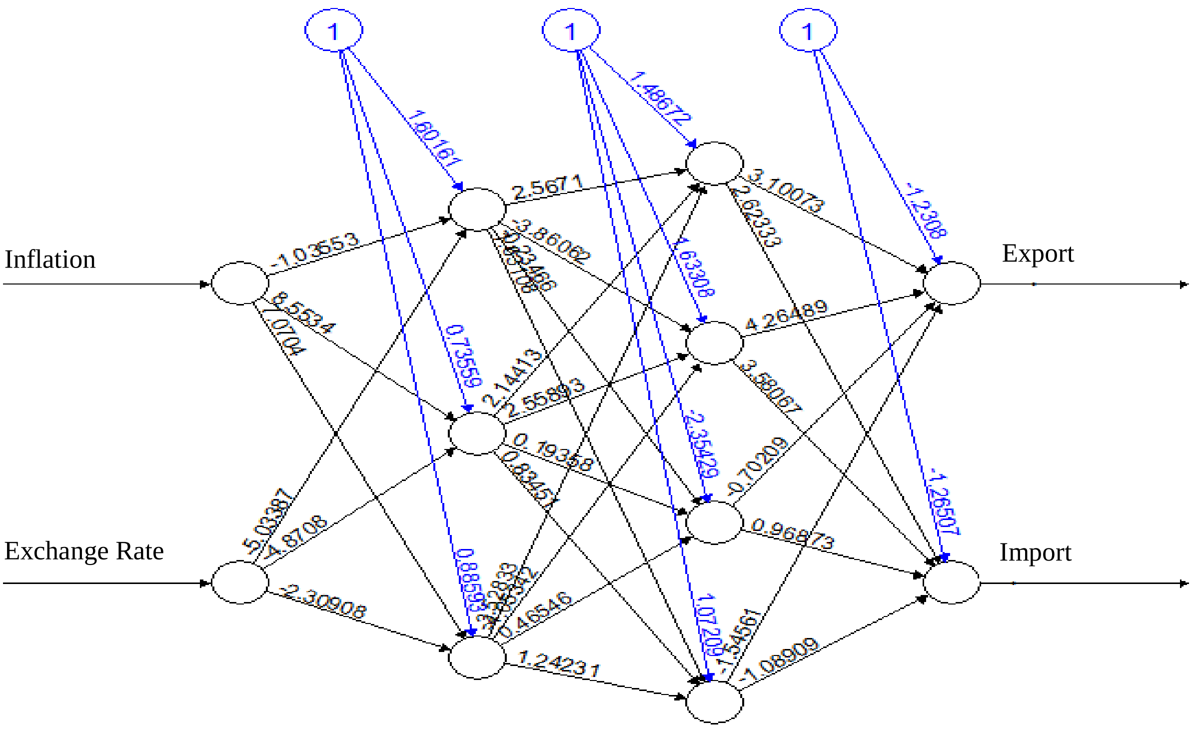

Figure. 7. Final Model Network Structure

Mathematically, the final model equation is written as:

$$\hat{y}_{t,m} = f^{(o)}\left(\sum_{k=1}^{K} v_{k,m}^{(o)} f^{(h_1)}\left(\sum_{j=1}^{J} v_{j,k,m}^{(h_2)} f^{(h_1)}\left(\sum_{i=1}^{p} v_{i,j,m}^{(h_1)} x_{i,t,m} + b_{j,m}^{(h_1)}\right) + b_{k,m}^{(h_2)}\right) + b_{m}^{(o)}\right) \quad (2)$$

where $m = 1{,}2$ shows the index for the first (export) and second (import) output. The weight and bias (b) parameters (v) for each output refers to the model architecture as in Figure 6.

3.6. Late Model Performance

Before carrying out the forecasting process, the model obtained must first go through a performance-checking stage to see the model's ability to predict actual data. Performance checking is done by calculating the prediction error rate using MAPE and by visually comparing actual and predicted data. The results of calculating the MAPE model obtained are presented in Table 8.

Table 8. Final Model MAPE

Outputs	MAPE
Y_1	13.76172
Y_2	13.62980

Based on Table 8, the MAPE of both outputs obtained values that are smaller than 20%. Thus, it can be concluded that the final model obtained can predict the actual data well.

After getting an interpretation based on calculating the error rate, visualization is then carried out to compare the actual output and the predictions. The visualization for each output 1 and 2 is presented in Figures 7 and 8 below.

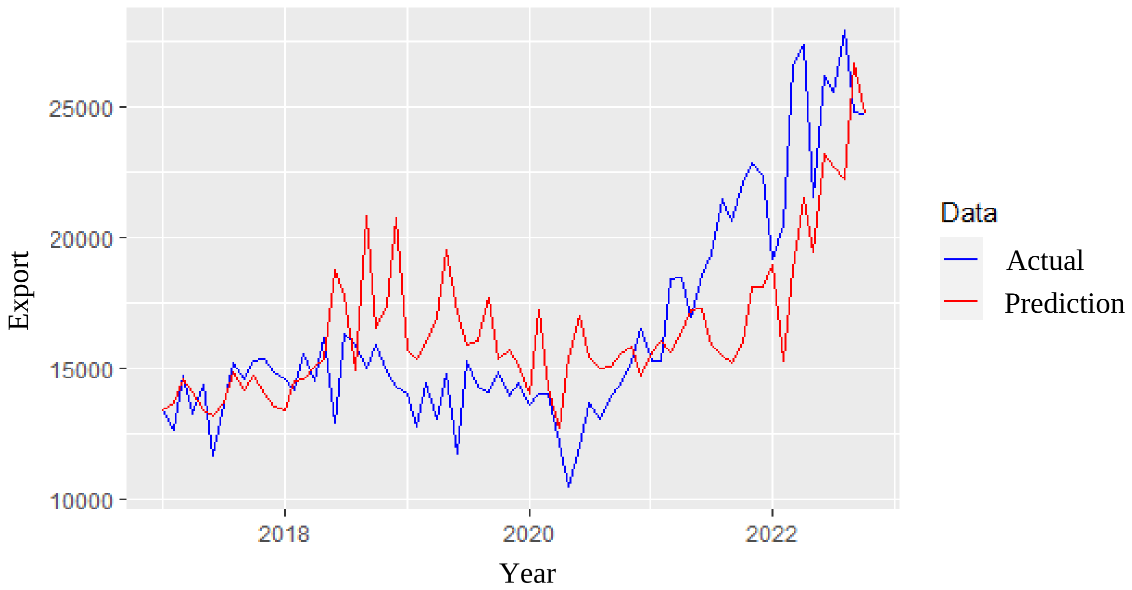

Figure. 8. Comparison of Actual and Predictions for Output 1

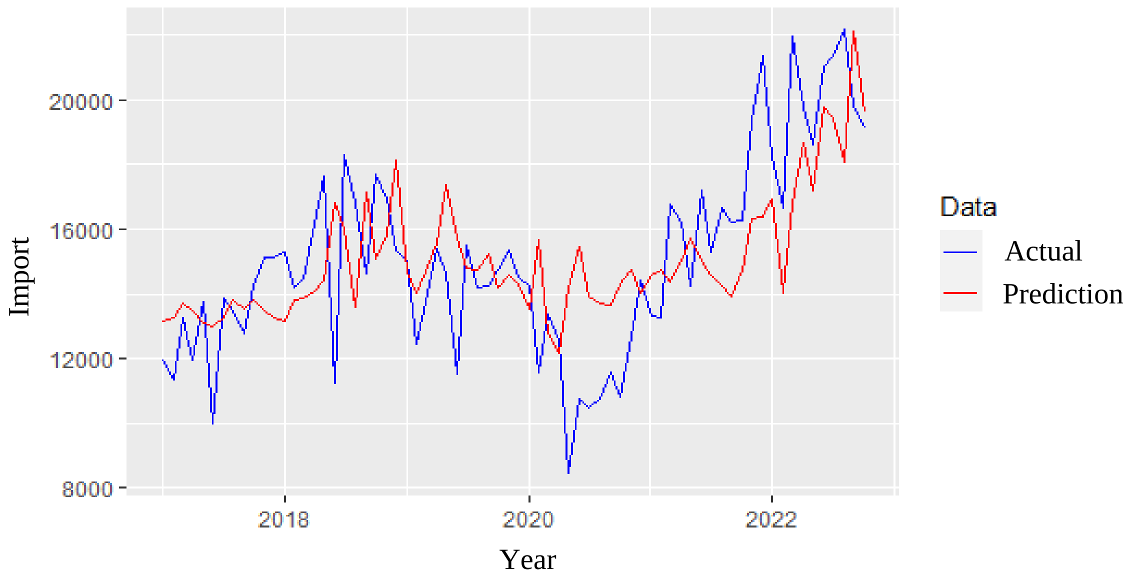

Figure. 9. Comparison of Actual and Predictions for Output 2

Based on Figure 8 and Figure 9, it can be seen that the model predictions are relatively able to follow the volatility pattern (pattern of ups and downs in data) which is quite fluctuating from the actual output.

Thus, it can be concluded that based on the level of prediction error and visualization the model has been able to predict actual data well.

3.7. Forecasting Model

After validating the final model structure based on Back-propagation DNN, forecasting is then carried out to obtain the current value of the output. The input variables used are the normalized values of inflation (X_1) and the exchange rate (X_2), the data of which are stated in Table 9 below.

Table 9. Forecasting Process Input

Inputs	Normalized Value
X_1	0.6181896
X_2	0.2500000

Based on the input listed in Table 9, a prediction (forecasting) is obtained for the output presented in Table 10 below.

Table 10. Forecasting Process Input

Outputs	Forecasting Value (Million US$)
Y_1	16208.13
Y_2	15105.33

3.8. Discussion

Forecasting statistical data that is multivariate (in this case called multi-output) generally has the assumption that the influence of predictors (in this case called input) must be linear, but in the case of real data, this assumption is difficult to fulfill. Therefore, modeling is carried out using DNN so that it can ignore linearity assumptions. DNN modeling cannot be done to interpret the influence of input on output, but rather to obtain the most accurate prediction values. In this research, modeling begins with linearity testing to ensure the urgency of using the DNN model. After that, the DNN modeling simulation process continues with a limit of the number of hidden layers of 2 and the number of nodes in each hidden layer of 2 to 4. Validation of the model used is by calculating the MAPE accuracy value for training and testing data, both of which must have a value below 20% so it can be categorized as a good prediction. After obtaining a model with these conditions, the model is applied to the full data (a combination of training and testing) and then used to forecast 1 data observation in the future which is stated in Table 10.

4. Conclusion

The study tested the potential of using Machine Learning methods, in particular Multi-Output Back-propagation DNN, to predict Indonesian exports and imports. The results of the research show that the model developed was able to predict export and import values with relatively low error rates, proving the effectiveness of this method in dealing with the complexity of multi-output data. This research provides potential applications in economic analysis, i.e. more accurate and responsive modeling to market conditions can be an important tool in strategic decision-making. The limitations of this research are the limitations on the quality and quantity of available data for further research, it is better to expand the scope of other machine learning methods or develop more complex models to improve the accuracy of predictions. This research provides a basis for a better understanding of Indonesia's international trade dynamics and the impact of economic policy on it.

Ethics approval

Not required.

Acknowledgments

Not required.

Competing interests

All the authors declare that there are no conflicts of interest.

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Underlying data

This research uses secondary data obtained from BPS- Statistics Indonesia and Yahoo Finance.

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