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Determining the Best Extreme Learning Machine Architecture for Indonesian Inflation Forecasting

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Abstract

Inflation is an indicator of a country's economic condition. Countries that have low inflation are countries with strong economies. High inflation is an indication that the economy is in trouble. Therefore, inflation forecasting is important to prevent economic problems in the country. Several studies show that machine learning algorithms are more efficient than econometric techniques. One of the machine learning algorithms for forecasting is the Extreme Learning Machine (ELM), namely an Artificial Neural Network (ANN) which has the advantages of the smallest training error, smallest weight norm, best performance and can be run very quickly. In ANN, determining the network architecture will determine forecasting accuracy. Therefore, the aim of this research is to determine the Extreme Learning machine architecture for inflation forecasting in Indonesia. The methods used are data collection, data preprocessing, data exploration, dividing data into training data and testing data, designing the ELM architecture, estimating ELM model weights for each architecture, calculating MSE and determining the best architecture for inflation forecasting. The result of this research is that the best model for Indonesian inflation data is the ELM model with input inflation lag 1, 2 and 5, Eid Al-Fitr indicator variables, and government policy indicator variables, the activation function is sigmoid and the number of neurons in the hidden layer is 10.

Keywords: artificial neural network, extreme learning machine, inflation forecasting, machine learning.

1. Introduction

One indicator of a country's economic condition is inflation. A country with low and stable inflation shows that the country has a strong economy. On the other hand, a country with high inflation and high volatility indicates that the country has an unhealthy economy. Therefore, inflation must always be kept under control, so that the value of future inflation needs to be predicted so that the government or related parties can immediately take the necessary actions to prevent rising inflation.

Research conducted by (1) shows that the money supply, exchange rate and fiscal deficits influence inflation in Zimbabwe. Research (2) shows that the money supply has an effect on inflation in India. Research results [3] state that the money supply affects inflation negatively and significantly in Nigeria. The results of this research are also in line with the results of research conducted by [4] but contrary to the results obtained by [5] . Meanwhile, [6] shows that the money supply and interest rate have an effect on inflation. Additionally, research [7] shows that bitcoin affects inflation.

Indonesia is a country with the majority of the population being Muslim. The tradition of Indonesian people is that they make a lot of purchases in the months around Eid al-Fitr, resulting in increased inflation in those months. Empirically, [8] shows that there is an effect of Eid al-Fitr on inflation in East Java. Apart from that, government policies such as setting increases in fuel oil (BBM) prices and increasing basic electricity tariffs also have an effect on increasing inflation.

Based on the previous explanation, the variables that are potential predictors of inflation are money supply, exchange rate, interest rate and bitcoin price. Apart from that, indicator variable that shows the existence of government policies to increase fuel prices is also potential predictor that can be used. For Indonesia, it is also necessary to add an indicator variable that shows the occurrence of Eid al-Fitr.

Extreme Learning Machine (ELM) is a feedforward artificial neural network (ANN) that has a single hidden layer. Artificial neural networks have been widely used in various fields because they can perform complex nonlinear mapping from input and are able to model natural phenomena that are difficult to handle with parametric techniques [9]. The advantages of ELM compared to other ANNs are that it has the smallest training error, smallest weight norm, best performance and can be run very quickly [10] .

A suitable ANN architecture will produce minimum errors. Determining the architecture means determining the number of inputs and what variables to use, the number of hidden layers, the number of neurons in each hidden layer and the activation function. According to [11], the variables used are the main determinants in determining the ANN architecture. Therefore, the aim of this research is to determine the ELM architecture for inflation forecasting based on several input variables.

2. Methodology

A. Extreme Learning Machine

Extreme Learning Machine (ELM) is an artificial neural network with a single hidden layer which has advantages compared to other artificial neural networks. The advantages of ELM include having the smallest training error, smallest weight norm, best performance and can be run very quickly [10]. Reference [12] and [13] show that ELM with randomly selected input weights can learn N different observations with small errors. In ELM there is no need to adjust the input weights and bias of the first hidden layer so the learning process is very fast and also produces good performance [14]. After the input weights and hidden bias are chosen randomly the ELM can be considered as a linear system and the output weights (the weights that connect the hidden layer to the output layer) of the ELM can be determined analytically through the general inverse operation of the output hidden layer matrix. According to [9], the ELM algorithm is as follows

Given a training set $\aleph = \{(\mathbf{x_i}, \mathbf{t}_i) | \mathbf{x}_i \in \mathbf{R}^n, \mathbf{t}_i \in \mathbf{R}^m, i = 1, 2, \dots, N\}$, activation function $g(x)$ and the number of hidden neuron $\tilde{N}$

Step 1. Randomly determine the input weight $\boldsymbol{w}_i$ and bias $b_i, i = 1,2, \dots, N$.

Step 2. Calculating the hidden layer output matrix $H(\boldsymbol{w_1}, \dots, \boldsymbol{w_{\tilde{N}}}, b_1, \dots, b_{\tilde{N}}, \boldsymbol{x_1}, \dots, \boldsymbol{x_{\tilde{N}}})$ where

$$\boldsymbol{H}(\boldsymbol{w_1}, \dots, \boldsymbol{w_{\tilde{N}}}, b_1, \dots, b_{\tilde{N}}, \boldsymbol{x_1}, \dots, \boldsymbol{x_{\tilde{N}}}) = \begin{bmatrix} g(\boldsymbol{w_1} \cdot \boldsymbol{x_1} + b_1) & \cdots & g(\boldsymbol{w_{\tilde{N}}} \cdot \boldsymbol{x_1} + b_{\tilde{N}}) \\ \vdots & \cdots & \vdots \\ g(\boldsymbol{w_1} \cdot \boldsymbol{x_N} + b_1) & \cdots & g(\boldsymbol{w_{\tilde{N}}} \cdot \boldsymbol{x_N} + b_{\tilde{N}}) \end{bmatrix}_N \quad 1$$

Step 3. Calculate the output weight β using the equation

$$\boldsymbol{\beta} = \mathbf{H}^{\dagger}\mathbf{T} \quad 2$$

where $\boldsymbol{\beta} = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_{\tilde{N}}^T \end{bmatrix}_{\tilde{N} \times m}$, $\boldsymbol{T} = \begin{bmatrix} \mathbf{t}_1^{\mathrm{T}} \\ \vdots \\ \mathbf{t}_{\mathrm{N}}^{\mathrm{T}} \end{bmatrix}_{N \times m}$, $\mathbf{H}^{\dagger}$ is general invers Moore – Penrose of **H.**

According to [15], the sigmoid activation function can be expressed as follows

$$g(x) = \frac{1}{1 + e^{-x}} \quad 3$$

An appropriate ANN architecture greatly determines the performance of the ANN. In general, designing an ANN architecture including ELM is determining the number of inputs and what variables to use, the number of hidden layers, the number of neurons in each hidden layer and the activation function. According to (11), the variables used are the main determinants in determining the ANN architecture. Therefore, it is necessary to study the input variables that will be used in ELM so that the ELM formed has good performance.

B. Data

The variables used in this research are inflation as output and inflation lag, money supply, exchange rate, interest rate and bitcoin price as input. Apart from that, indicator variables indicating the existence of government policy to increase fuel prices and basic electricity tariffs and indicator variables indicating the occurrence of Eid al-Fitr are also used as input. Data on inflation, money supply and interest rate were obtained from bi.go.id. Exchange rate was obtained from kaggle.com.

C. Step of Research

The steps for this research are as follows

1. Data collection
2. Preprocessing data, namely completing empty data and standardizing data on input variables using min – max scaler

Using equation *4*

$$y_{new} = \frac{y_{old} - min}{max \ - min} \quad 4$$

3. Explore the data by forming a plot of inflation to find out the patterns contained in the

data and special characteristics that may exist in the data

4. Determine PACF, which can be calculated recursively starting from $\hat{\phi}_{11} = \hat{\rho}_1$ and $\hat{\phi}_{kk}$ can be calculated using equation 5

$$\hat{\phi}_{k+1,k+1} = \frac{\hat{\rho}_{k+1} - \sum_{j=1}^{k} \hat{\phi}_{kj}\hat{\rho}_{k+1-j}}{1 - \sum_{j=1}^{k} \hat{\phi}_{kj}\hat{\rho}_j} \qquad 5$$

and

$$\hat{\phi}_{k+1,j} = \hat{\phi}_{kj} - \hat{\phi}_{k+1,k+1}\hat{\phi}_{k,k+1-j}, \quad j = 1, 2, \dots, k \qquad 6$$

where

$$\hat{\rho}_k = \frac{\sum_{t=1}^{n-k}(Y_t - \bar{Y})(Y_{t+k} - \bar{Y})}{\sum_{t=1}^{n}(Y_t - \bar{Y})^2}, \quad k = 0, 1, 2, \dots \qquad 7$$

5. Divide the data into two with a ratio of 80% for training data and 20% for testing data

6. Design the Extreme Learning Machine architecture

7. Estimating weights on ELM as in equation *2*

8. Calculate the Mean Square Error (MSE) of each ELM architecture using equation 8

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 \qquad 8$$

3. Result and Discussion

A plot of Indonesian inflation data for the period April 2013 to January 2023 is presented in Figure 1. This figure shows that Indonesia's inflation value fluctuates around the value 0 to 1. However, in 2013, to be precise in July 2013, inflation increased to 3.29. This is due to an increase in fuel prices, namely the premium price increased from IDR 4,500 per liter to IDR 6,500 per liter and the price of diesel increased from IDR 4,500 per liter to IDR 5,500 per liter. This caused an increase in inflation in July 2013, although in August 2013 inflation fell again to around 1. The increase in inflation occurred again in 2014, namely in December. This increase in inflation was also triggered by an increase in fuel prices in November 2014, namely an increase in premium prices from IDR 6,500 per liter to IDR 8,500 per liter and an increase in the price of diesel from IDR 5,500 per liter to IDR 7,500 per liter. This needs to be considered in determining inputs in modeling for inflation forecasting.

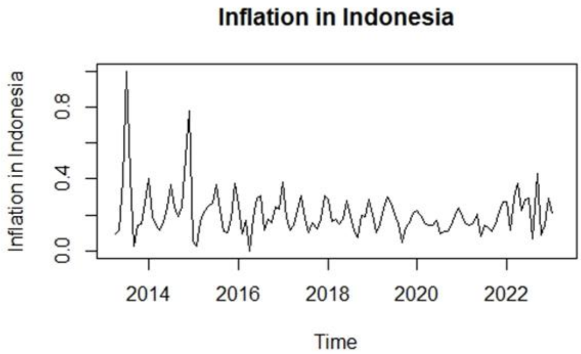

Figure 1. Plot of Inflation of Indonesia

In time series modeling, the most frequently used input is the lag of the variable of interest. To determine the inflation lag that will be used as input, the Partial Autocorrelation Function (PACF) is used. The PACF plot is presented in Figure 2. The figure shows that the significant lags are lags 1, 2 and 5. Therefore inflation lags 1, 2 and 5 are used as input in inflation modeling using ELM.

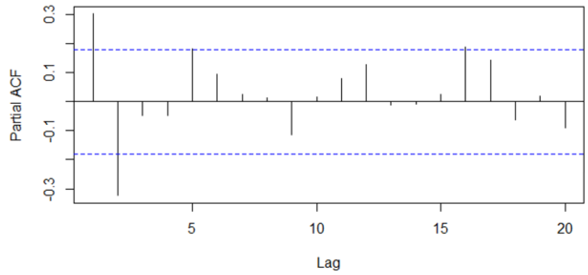

Figure 2. Plot of Partial Autocorrelation

Based on PACF, data exploration, and previous research, the input used and the ELM architecture are presented in

Table **1**

Table 1. Input and the ELM Architecture

Input	**Activation Function**	**Number of Neuron in Hidden Layer**	**Data**	**MSE**
Inflation Lag 1, 2, and 5	Sigmoid Biner	5	Training	**<u>0.115</u>**
			Testing	**<u>0.152</u>**
		10	Training	0.095
			Testing	0.168
		15	Training	0.067

Input	Activation Function	Number of Neuron in Hidden Layer	Data	MSE
			Testing	0.249
	Tan Hyperbolic	5	Training	**0.116**
			Testing	**0.168**
		10	Training	0.087
			Testing	0.228
		15	Training	0.061
			Testing	0.195
Inflation Lag 1, 2, and 5, Indicator Variable of Eid al Fitr, Indicator Variable of Government Policies	Sigmoid Biner	5	Training	0.099
			Testing	0.176
		10	Training	**0.086**
			Testing	**0.145**
		15	Training	0.081
			Testing	0.163
	Tan Hyperbolic	5	Training	**0.111**
			Testing	**0.169**
		10	Training	0.074
			Testing	0.186
		15	Training	0.077
			Testing	0.178
Inflation Lag 1, 2, and 5, Indicator Variable of Eid al Fitr, Indicator Variable of Government Policies, money supply, Interest Rate, Exchange Rate, Bitcoin Price,	Sigmoid Biner	5	Training	0.132
			Testing	0.171
		10	Training	0.100
			Testing	0.169
		15	Training	**0.086**
			Testing	**0.141**
	Tan Hyperbolic	5	Training	**0.147**
			Testing	**0.146**
		10	Training	0.106
			Testing	0.172
		15	Training	0.094
			Testing	0.172

Table **1** shows that there are 2 ELM models that have the smallest MSE (with a value of 0.086). The first model is the ELM model with input inflation lags 1, 2 and 5, the Eid Al-Fitr holiday indicator variable, and the government policy indicator variable, the activation function is sigmoid and the number of neurons in the hidden layer is 10. The second model is the ELM model with inflation input Lags 1, 2 and 5, Eid Al-Fitr indicator variables, government policy indicator variables, money supply, interest rate, exchange rate, and bitcoin price, sigmoid activation function, and the number of neurons in the hidden layer is 15. Model 1 has input fewer and the number of neurons in the hidden layer is also less than model 2 so model 1 is a simpler model than model 2 but has the same model goodness. Therefore, model 1 was chosen as the best model. Next, the plot of actual data and predicted data is presented in Figure 3.

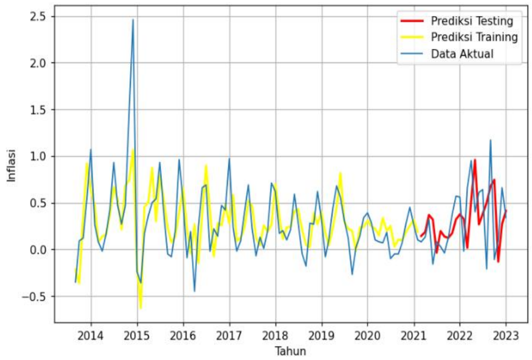

Figure 3. Plot of Actual Data and Prediction Data

Figure 3 shows that the predicted data in the training data is quite close to the actual data. It's just that when inflation rose too high, namely in December 2014, the predicted data was quite far from the actual data. The predicted data in the testing data is also quite close to the actual data. The best model obtained is not able to predict well if the data rises too high.

4. Conclusion

The conclusion obtained from this research is that the best model for Indonesian inflation data is the ELM model with input Lag Inflation 1, 2 and 5, Eid Al-Fitr Indicator Variables, and Government Policy Indicator Variables, the activation function is sigmoid and the number of neurons in the hidden layer is 10. However, this model is not yet able to predict inflation that will rise too high. Therefore, it is necessary to determine input that can capture high changes.

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