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Time Series Forecasting with Ensemble Methods for Inflation in Indonesia

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Abstract **– Inflation is an economic problem experienced by almost all countries in the world so inflation needs to be controlled. Controlling inflation requires accurate inflation forecasting. In this study, the ensemble method was used for the modeling. Three ensemble methods were tested, namely simple average, trimmed average and variance-based. The individual models applied in this research are based on Machine Learning, which include Long Short-Term Memory (LSTM), Extreme Learning Machine (ELM), and Feed Forward Neural Network (FFNN). In selecting inputs for individual models, statistical tools were used, namely correlation analysis and partial autocorrelation function. Among the three individual models, the best model was the FFNN model. While the best ensemble method was variance-based. The ensemble method can reduce the RMSE of the best individual model.**

Keywords **– Ensemble Time Series, Indonesian inflation, Long Short-Term Memory, Extreme Learning Machine, Feed Forward Neural Network.**

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1. Introduction

Bank Indonesia stated that inflation is a tendency for prices to increase in general and continuously. Inflation is a global economic challenge faced by most countries in the world, including Indonesia. Low inflation is the hope of all countries because high inflation will cause various problems for the people. Inflation needs to be controlled so that the country's economy is healthy and strong. Controlling inflation requires accurate inflation forecasting so that parties involved in controlling inflation can take the necessary actions.

To predict inflation, it is necessary to know the causes of inflation. Inflation is caused by several things, namely increasing production costs (cost push inflation), increasing demand for goods and services (demand pull inflation), and the money supply. Increasing production costs over a certain period of time continuously cause inflation to increase. Increasing production costs can be caused by rising foreign exchange rates which result in expensive raw materials from abroad. Research on this has been conducted by [1], [2], [3]. Research [4] also shows that changes in the value of crypto currencies such as bitcoin can affect inflation. Inflation in trading partner countries can also affect inflation because raw materials from abroad become expensive. Other increases in production costs that can cause inflation are increases in fuel prices and increases in basic electricity rates [5], [6], [7]. Meanwhile, increasing demand can be caused by religious celebrations such as Eid al-Fitr. Research [8] shows that Eid al-Fitr can increase inflation in Indonesia. Increasing interest rates will cause inflation to fall because people prefer to save rather than spend. Research on this matter has been conducted by [9], [10], [11]. The increasing money supply will cause increasing inflation (Quantity Theory Inflation). This has been researched in various parts of the world by [1], [8], [11], [12], [13].

Many studies have been conducted to obtain models used for inflation forecasting, both modeling from statistical approaches and machine learning approaches. Modeling for inflation forecasting is quite complex because it involves many variables and is less suitable if using a statistical approach. Machine learning techniques have been extensively utilized for inflation forecasting. This is supported by research [14], which shows that machine learning methods have superior performance compared to statistical approaches in predicting inflation in the United States. Other studies that use the machine learning approach for inflation forecasting are [15], [16], and [17]. These studies show that models with a machine learning approach produce accurate predictions. However, the use of ensemble techniques, which combine predictions from various methods, has proven effective in improving forecast accuracy, as stated by [18], [19], [20], [21]. Therefore, this study will use the ensemble method of models with a machine learning approach to model inflation in Indonesia.

2. Methodology

In this study, several variables were used, namely Indonesian inflation and several variables that are suspected of influencing Indonesian inflation. The variables that are suspected of influencing Indonesian inflation are inflation from several countries that have trade relations with Indonesia, namely Chinese inflation, United Kingdom inflation and European Union inflation. Another variable that influences Indonesian inflation is the exchange rate. In this study, the exchange rates of China, US, European Union and UK currencies were used. In addition, the variables that will be used as input are the money supply, interest rates, bitcoin prices, indicators of fuel price increases and indicators of Eid celebrations. Data from each variable is monthly data from April 2013 to March 2024. Indonesian inflation data was obtained from bps.go.id, as was data on the money supply and interest rates. Meanwhile, China inflation data, US inflation, European Union inflation and bitcoin prices were obtained from www.statista.com and IDR exchange rates were obtained from bi.go.id.

Before being analyzed, data transformation was carried out so that the data scale was more uniform using Equation (1).

$$y_{new} = \frac{y_{old} - min}{max - min} \tag{1}$$

Next, the data is partitioned into two parts with a proportion of 80% as training data and 20% as testing data.

Ensemble is a combination of several individual models. In this study, the individual models used are machine learning-based models for time series data, namely long Short-Term Memory (LSTM), Extreme Learning Machine (ELM) and Feed Forward Neural Network (FFNN).

Long Short-Term Memory (LSTM): Long Short-Term Memory (LSTM), developed by [22], is a variant of the Recurrent Neural Network (RNN) architecture. The main advantage of this model is its ability to overcome the vanishing gradient problem, making it effective for predicting time series data and other sequential data. The LSTM architecture has a unit called a memory cell that is controlled by three main gates, namely the forget gate, input gate, and output gate. Specifically, the forget gate functions to select information that needs to be kept or discarded. This mechanism uses a sigmoid function that produces a value between 0 (discarding all information) to 1 (retaining all information), as formulated in Equation (2).

$$f_t = \sigma\left(W_f . [l_{t-1}, y_t] + b_f\right) \tag{2}$$

Where:

f_t	:	forget gate current period or time, where the range of values is (0,1)
W_f	:	Weight of forget gate
l_{t-1}	:	the output value of processing in a previous period or time
b_f	:	bias value applied to the forget gate
y_t	:	input value for the current period or time

The input gate is responsible for regulating which new information is added to the memory cell state. This mechanism comprises two distinct parts: a sigmoid layer that identifies the values to be updated, and a tanh layer that generates a vector of new candidate values. The sigmoid function is defined in the Equation (3)

$$i_t = \sigma(W_i . [l_{t-1}, y_t] + b_i) \tag{3}$$

and the tanh function is presented in the Equation (4).

$$C_t' = \tanh(W_c . [l_{t-1}, y_t] + b_c) \tag{4}$$

Where according to [23]

$$\sigma(x) = \frac{1}{1 + exp(-x)} \tag{5}$$

and

$$tanh(x) = \frac{\exp(2x) - 1}{\exp(2x) + 1} \tag{6}$$

i_t	:	input gate current period or time, where the range of values is (0,1)
C_t'	:	candidate cell at the current gate input period or time

W_i : weight of input gate
W_c : weight of candidate cells at gate input
b_i : bias value applied to the input gate
b_c : bias value applied to the gate input candidate cells

The Output Gate governs which specific portion of the memory cell state contribute to the current output. The process of adjusting cell values or model parameters at the current timestep using Equation (7).

$$C_t = f_t \times C_{t-1} + i_t \times C_t' \quad (7)$$

The output values are presented in the equation (8)

$$O_t = \sigma(W_o [l_{t-1}, y_t] + b_o) \quad (8)$$

Where:

O_t : output gate period or current time, where the range of values is (0,1)
W_o : weight of output gate
b_o : bias value applied to the gate output

The final LSTM output value is derived from the output gate, as calculated in Equation (9).

$$l_t = O_t \times \tanh(C_t) \quad (9)$$

Extreme Learning Machine: Extreme Learning Machine (ELM) is an artificial neural network architecture categorized as a Single Hidden Layer Feedforward Network (SLFN). This model structure consists of three main layers: an input layer, one hidden layer, and an output layer. One of the unique characteristics of ELM is that it does not use the backpropagation algorithm for weight updates. In this method, input weights and biases are initialized randomly, while output weights are calculated using a direct analytical solution. The ELM algorithm according to [24] is as follows:

For a defined 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 a specified number of hidden neurons $\widetilde{N}$, the procedure is executed as follows:

1. Randomly initialize the input weights $\boldsymbol{w}_i$ and biases $b_i, i = 1,2, \dots, N$
2. Compute the hidden layer matrix

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

3. Calculate the output weight $\boldsymbol{\beta}$ utilizing Equation 10.

$$\boldsymbol{\beta} = \mathbf{H}^{\dagger}\mathbf{T} \quad (10)$$

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

Feed Forward Neural Network: Referring to [30], Feed Forward Neural Network (FFNN) is defined as a type of Artificial Neural Network (ANN) that has the characteristic of unidirectional information flow. Data moves from the input layer to the output without any cycles or feedback loops. In this study, the FFNN architecture is specifically designed with an output layer that contains inflation prediction variables. The input layer contains inflation lag variables and several inflation-causing variables (for example, there are p variables in total, namely $x_1, x_2, \dots, x_p]$. If it is determined that there are h hidden units, then the weight matrix (network parameters) in the hidden layer will have dimensions $p \times h$ where:

$$\boldsymbol{w} = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1h} \\ w_{21} & w_{22} & \cdots & w_{2h} \\ \vdots & \vdots & \ddots & \vdots \\ w_{p1} & w_{p2} & \cdots & w_{ph} \end{bmatrix}$$

The architecture incorporates constant input units connected to every neuron within both the hidden and output layers. This configuration yields a bias vector $\boldsymbol{\alpha} = (\alpha_1, \alpha_2, \dots, \alpha_h)'$ for the hidden layer and $\boldsymbol{\beta} = (\beta_1, \beta_2, \dots, \beta_h)'$ for the output layer. Given that the output layer consists of a single variable, its corresponding weight matrix is designated as

$$\boldsymbol{\lambda} = [\lambda_{11} \quad \lambda_{12} \quad \cdots \quad \lambda_{1h}]$$

Consequently, the final output of the FFNN architecture is mathematically expressed as:

$$\boldsymbol{y_t} = \boldsymbol{\lambda} F((\boldsymbol{xw})' + \boldsymbol{\alpha}) + \boldsymbol{\beta} + \boldsymbol{\varepsilon}_t \quad (11)$$

Where:

$$F((\boldsymbol{xw})' + \boldsymbol{\alpha}) = \frac{1}{1 + exp\left(-((\boldsymbol{xw})' + \boldsymbol{\alpha})\right)}$$

Each individual model, whether LSTM, ELM or FFNN, requires input to be processed. In selecting the input to be used in the individual model, statistical tools are used, namely correlation analysis and partial autocorrelation function (PACF) analysis. PACF has been widely used to determine the lag variable (in this case, Indonesian inflation) that will be used as input or as a predictor variable in time series analysis such as ARIMA. Correlation analysis is useful for determining candidate variables that have a significant relationship with Indonesian inflation.

The correlation coefficient of X and Y is determined by the equation below:

$$r_{XY} = \frac{n\sum_{i=1}^{n} X_i Y_i - \sum_{i=1}^{n} X_i \sum_{i=1}^{n} Y_i}{\sqrt{n\sum_{i=1}^{n} X_i^2 - \left(\sum_{i=1}^{n} X_i\right)^2}\sqrt{n\sum_{i=1}^{n} Y_i^2 - \left(\sum_{i=1}^{n} Y_i\right)^2}} \quad (12)$$

To test whether the correlation is significant, the hypothesis is used

$$H_0: \rho_{XY} = 0$$
$$H_1: \rho_{XY} \neq 0$$

Test statistics

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} \quad (13)$$

where $t \sim t-$ student with $df = n-2$.

According to [25], The PACF is computed recursively, initiating with $\hat{\phi}_{11} = \hat{\rho}_1$ while $\hat{\phi}_{kk}$ is subsequently derived using Equation (14)

$$\hat{\phi}_{k+1,k+1} = \frac{\hat{\rho}_{k+1} - \sum_{j=1}^{k} \hat{\phi}_{kj}\hat{\rho}_{k+1-j}}{1 - \sum_{j=1}^{k} \hat{\phi}_{kj}\hat{\rho}_j} \quad (14)$$

and equation (15)

$$\hat{\phi}_{k+1,j} = \hat{\phi}_{kj} - \hat{\phi}_{k+1,k+1}\hat{\phi}_{k,k+1-j}, \quad j = 1, 2, \ldots, k \quad (15)$$

Where:

$$\hat{\rho}_k = \frac{\sum_{t=1}^{n-k}(Y_t - \bar{Y})(Y_{t+k} - \bar{Y})}{\sum_{t=1}^{n}(Y_t - \bar{Y})^2}, \ k = 0, 1, 2, \ldots \quad (16)$$

$\hat{\phi}_{kk}$ significant if $|\hat{\phi}_{kk}| > \frac{2}{\sqrt{n}}$

Ensemble Method: The ensemble method is a method of combining predictions from several models to increase prediction accuracy. Several ensemble methods for time series have been developed. In this study, three methods were used, which will be compared for their accuracy, namely simple average, trimmed average and variance-based.

Let $\boldsymbol{Y} = \{y_1, y_2, \ldots, y_T\}$ denote the actual time series and $\widehat{\boldsymbol{Y}}^{(i)} = \left\{\hat{y}_1^{(i)}, \hat{y}_2^{(i)}, \ldots, \hat{y}_T^{(i)}\right\}$ represent the forecast generated by the i^{th} method $(i = 1, 2, \ldots, I)$. By linearly combining these individual forecasts, an ensemble forecast is constructed.

The resulting ensemble forecast series is given by

$$\widehat{\boldsymbol{Y}}^{(c)} = \left\{\hat{y}_1^{(c)}, \hat{y}_2^{(c)}, \ldots, \hat{y}_T^{(c)}\right\} \quad (17)$$

where

$$\hat{y}_t^{(c)} = w_1\hat{y}_t^{(1)} + w_2\hat{y}_t^{(2)} + \cdots + w_I\hat{y}_t^{(I)} = \sum_{i=1}^{I} w_i\hat{y}_t^{(i)} \quad (18)$$

$\forall t = 1,2, \ldots, T$

Where w_i denotes the weight assigned to the i^{th} forecasting method.

- In the simple average, each model is given the same weight, i.e. $w_i = \frac{1}{I}, i = 1,2, \ldots, I$)
- In the trimmed average, k% of the worst models are not used. Then the average of the forecasts from the remaining models is calculated. Generally, k is used between 10 - 30. The trimmed method can be used if $I \geq 3$
- In the variance-based method, the optimal weight is derived by minimizing the total Sum of Squared Error.

Model selection is based on the Root Mean Square Error (RMSE), calculated using the formula presented in the Equation (19).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2} \quad (19)$$

3. Results

The preliminary stage of time series analysis involves data exploration to uncover the inherent characteristics and patterns within the dataset. Figure 1 illustrates the graphical representation of the inflation data.

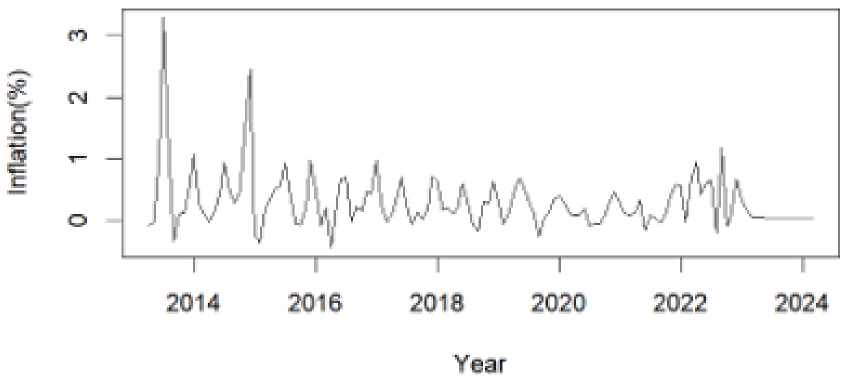


Figure 1. Plot of Indonesia inflation from April 2013 to March 2024

Figure 1 illustrates a generally horizontal trend, punctuated by periods of elevated inflation specifically in July 2013 and December 2014. These spikes were driven by external shocks; the surge in July 2013 was a response to the fuel price hike in June 2013, while the high inflation in December 2014 resulted from a similar increase in November 2014.

Therefore, the indicator variable for the increase in fuel prices needs to be included as input in the inflation model. Next, correlation analysis and Partial Autocorrelation Function (PACF) analysis are performed. Correlation analysis is used to determine variables that affect inflation, PACF is used to determine the inflation lag entered as input.

Figure 2 illustrates the Partial Autocorrelation Function (PACF) plot.

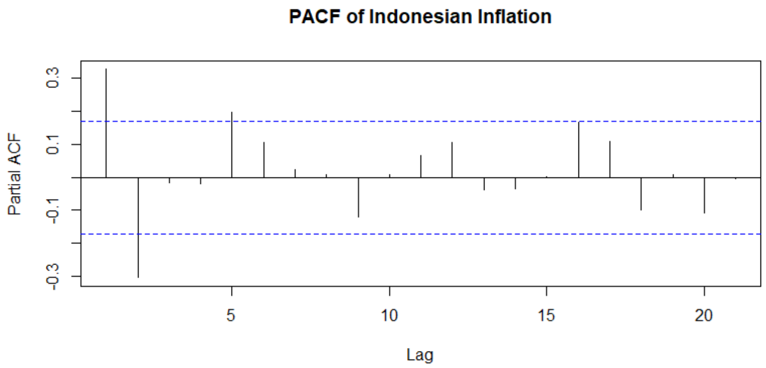
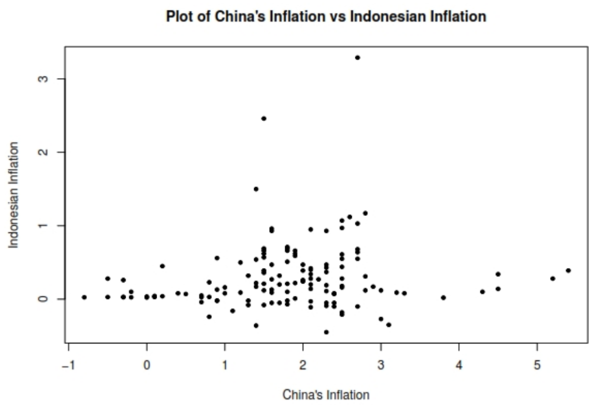


Figure 2. Indonesian inflation PACF plot

Figure 2 shows that lag 1, 2, and 5 are statistically significant. So that inflation lags 1, 2, and 5 are used as input. Furthermore, Figure 3 illustrates the relationship between Indonesian inflation and its potential determinants (suspected influencing variables).



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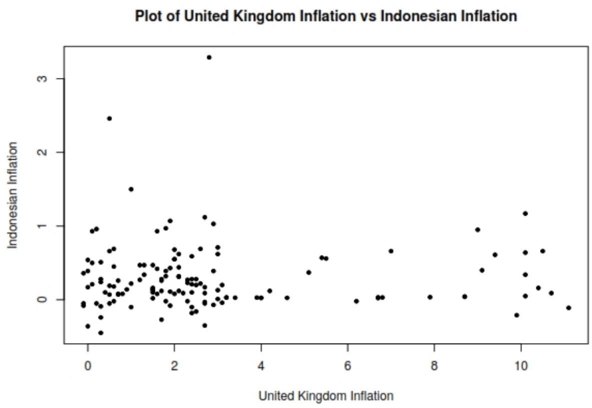

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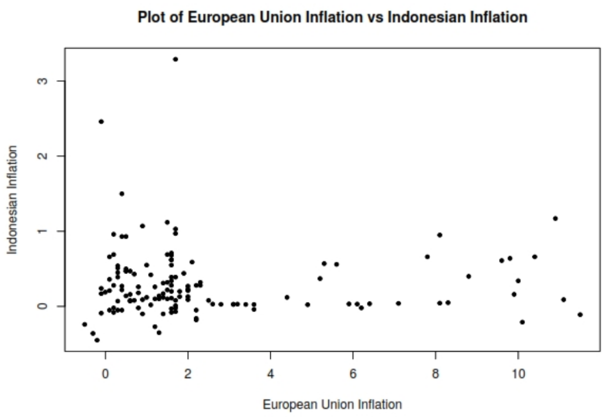
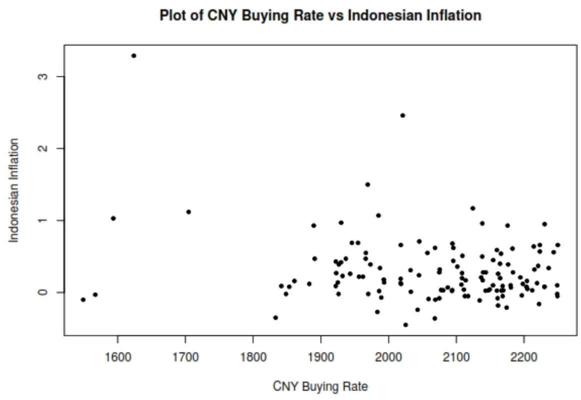


c)

Figure 3. Scatter Plot between Indonesia inflation and a) China inflation b) UK inflation c) EU inflation

Figure 3 shows a very weak relationship between Indonesian inflation and Chinese inflation, UK inflation, and EU inflation. Furthermore, Figure 4 illustrates the relationship between Indonesian inflation and the exchange rate.



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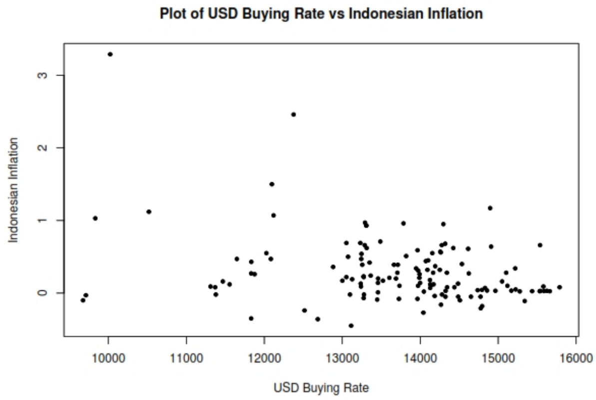

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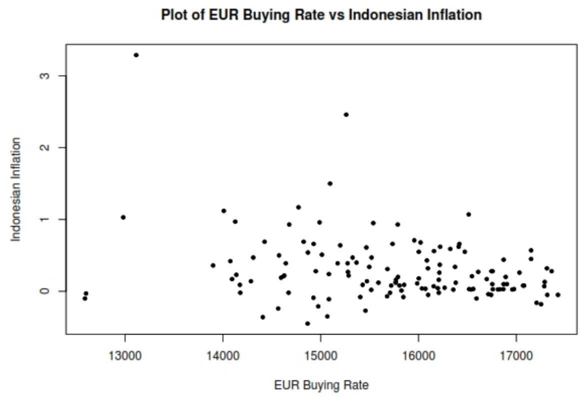

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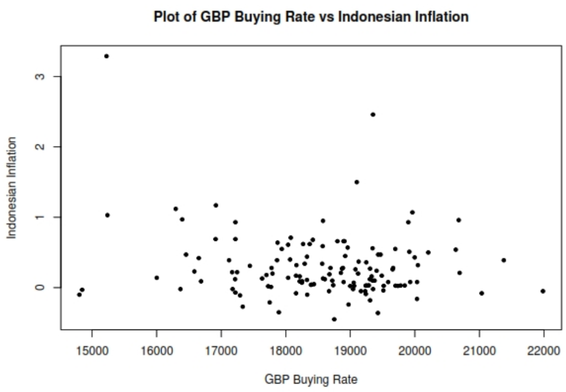
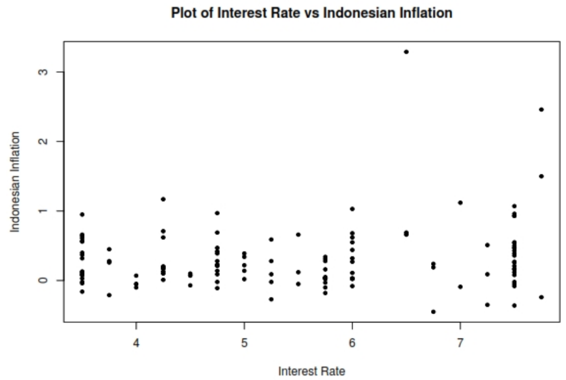


d)

Figure 4. Scatter plot between Indonesian inflation and exchange rates of a) Chinese currency b) US currency c) EU currency d) UK currency

Figure 4 indicates a relationship, albeit a weak one, between Indonesian inflation and the exchange rates of China, the US, the European Union, and the UK. Additionally, Figure 5 presents scatter plots analyzing the correlation between inflation and interest rates, money supply, and Bitcoin prices.



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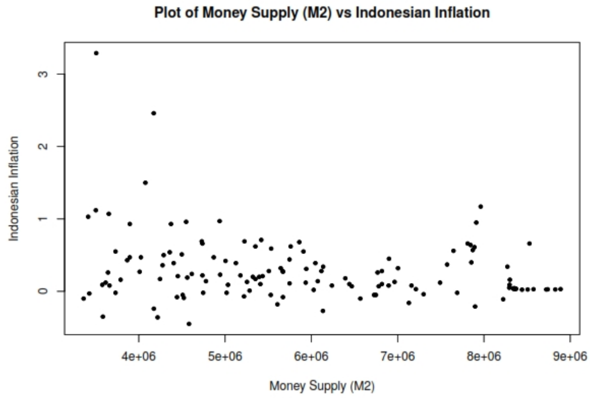

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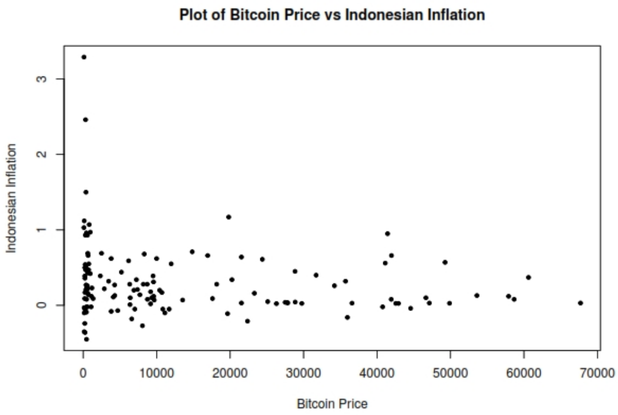

c)

Figure 5. Scatter plot between Indonesian inflation and a) interest rate b) money supply c) bitcoin price

Figure 5 shows a weak relationship between Indonesian inflation and interest rates, money supply and bitcoin prices. Correlation analysis was conducted to validate the relationship between Indonesian inflation and the designated input variables.

The correlation coefficient and p-value are presented in Table 1.

Table 1. Correlation coefficient of Indonesian inflation with candidate input variables

	Correlation Coefficient	*p-value*
Indonesian Inflation –China Inflation	0.1469	0.0928
Indonesian Inflation – European Union Inflation	-0.0069	0.9375
Indonesian Inflation – UK Inflation	0.0016	0.9858
Indonesian Inflation – China Currency Exchange Rate	-0.2292	0.0082
Indonesian Inflation – EU Currency Exchange Rate	-0.2733	0.0015
Indonesian Inflation –US Currency Exchange Rate	-0.3091	0.0003
Indonesian Inflation – UK Currency Exchange Rate	-0.1706	0.0505
Indonesian Inflation – Money Supply	-0.2307	0.0078
Indonesian Inflation – Interest Rate	0.1614	0.0644
Indonesian Inflation –Bitcoin Price (USD)	-0.1595	0.0677

Based on Table 1, utilizing a significance level (alpha) of 10%, it is evident that Indonesian inflation is significantly correlated with Chinese inflation, various exchange rates (China, EU, US, and UK), money supply, interest rates, and Bitcoin prices.

Based on the correlation analysis and PACF, there are 6 input schemes used in this study. Schemes 1 and 2 use only inflation lag input. Scheme 1 uses inflation lag 1, 2, and 5 as input, while scheme 2 uses inflation lag 1 to lag 5 as input. Schemes 3 and 4 use inflation lag input and domestic variables only, namely the money supply, interest rates, Eid el Fitr indicators and fuel price increase indicators. Schemes 5 and 6 use inflation lag input, domestic variables (money supply, interest rates, Eid el Fitr indicators and fuel price increase indicators) and foreign (Chinese inflation, Chinese currency exchange rates, the European Union, the US and the UK, and bitcoin prices).

Subsequently, the modeling phase employs LSTM, ELM, and FFNN architectures. Specifically for the LSTM model, the experimental design investigates configurations with both single and double hidden layers. The number of neurons within these layers was varied across a range of 5, 15, 25, 35, 50, 75, and 100. The optimal LSTM results derived from each scheme are detailed in Table 2.

Table 2. RMSE of the best LSTM Modeling on each input scheme

No	Input	Number of Hidden Layer	Number of Neuron in Hidden Layer	RMSE	
				Training Data	Testing Data
1.	Indonesian Inflation lag 1,2 5	1	15	0.313	0.407
2.	Indonesian Inflation lag 1 to lag 5	1	50	0.311	0.417
3.	Indonesian Inflation lag 1,2,5, Money Supply, Interest Rate, Indicator of Eid el Fitr, Indicator of government policy	1	50	0.265	0.426
4.	Indonesian Inflation lag 1 to lag 5, Money Supply, Interest Rate, Indicator of Eid el Fitr, Indicator of government policy	1	75	0.185	0.308
5.	Indonesian Inflation Lag 1, Lag 2 and Lag 5, Money Supply, Interest Rate, Indicator of Eid el Fitr, Indicator of government policy, China Inflation, China Exchange Rate, EU Exchange Rate, US Exchange Rate, UK Exchange Rate, Bitcoin Price	1	25	0.293	0.379
6.	Indonesian Inflation Lag 1 to lag 5, Money Supply, Interest Rate, Indicator of Eid el Fitr, Indicator of government policy, China Inflation, China Exchange Rate, EU Exchange Rate, US Exchange Rate, UK Exchange Rate, Bitcoin Price	2	35	0.310	0.427

In the ELM model, the hidden layer neuron counts were tested across a range of 5, 15, 25, 35, 50, 75, and 100.

The optimal modeling results derived from each of these schemes are displayed in Table 3.

Table 3. RMSE of the best ELM Modeling on each input scheme

No	Input	Number of Neuron in Hidden Layer	RMSE	
			Training Data	Testing Data
1.	Indonesian Inflation lag 1,2 5	35	0.144	0.812
2.	Indonesian Inflation lag 1 to lag 5	25	0.181	0.487
3.	Indonesian Inflation lag 1,2,5, Money Supply, Interest Rate, Indicator of Eid el Fitr, Indicator of government policy	20	0.188	0.492
4.	Indonesian Inflation lag 1 to lag 5, Money Supply, Interest Rate, Indicator of Eid el Fitr, Indicator of government policy	25	0.168	0.514
5.	Indonesian Inflation Lag 1, Lag 2 and Lag 5, Money Supply, Interest Rate, Indicator of Eid el Fitr, Indicator of government policy, China Inflation, China Exchange Rate, EU Exchange Rate, US Exchange Rate, UK Exchange Rate, Bitcoin Price	25	0.193	0.554
6.	Indonesian Inflation Lag 1 to lag 5, Money Supply, Interest Rate, Indicator of Eid el Fitr, Indicator of government policy, China Inflation, China Exchange Rate, EU Exchange Rate, US Exchange Rate, UK Exchange Rate, Bitcoin Price	25	0.187	0.336

The FFNN modeling process evaluated architectures with both single and double hidden layers. Neuron counts within these layers were varied across a set range (5, 15, 25, 35, 50, 75, and 100), utilizing both linear and sigmoid activation functions.

The optimal results for each FFNN scheme are detailed in Table 4.

Table 4. RMSE of the best FFNN Modeling on each input scheme

No	Input	Number of Hidden Layer	Number of Neurons in Hidden Layer	Aktivation Func	RMSE	
					Training Data	Testing Data
1.	Indonesian Inflation lag 1,2 5	1	35	linear	0.330	0.440
2.	Indonesian Inflatio lag 1 to lag 5	1	50	sigmoid	0.220	0.460
3.	Indonesian Inflation lag 1,2,5, Money Supply, Interest Rate, Indicator of Eid el Fitr, Indicator of government policy	1	15	sigmoid	0.360	0.270
4.	Indonesian Inflation lag 1 to lag 5, Money Supply, Interest Rate, Indicator of Eid el Fitr, Indicator of government policy	1	5	linear	0.380	0.350
5.	Indonesian Inflation Lag 1, Lag 2 and Lag 5, Money Supply, Interest Rate, Indicator of Eid el Fitr, Indicator of government policy, China Inflation, China Exchange Rate, EU Exchange Rate, US Exchange Rate, UK Exchange Rate, Bitcoin Price	1	35	sigmoid	0.300	0.380
6.	Indonesian Inflation Lag 1 to lag 5, Money Supply, Interest Rate, Indicator of Eid el Fitr, Indicator of government policy, China Inflation, China Exchange Rate, EU Exchange Rate, US Exchange Rate, UK Exchange Rate, Bitcoin Price	1	10	linear	0.360	0.340

After obtaining 18 individual models, namely 3 models (LSTM, ELM and FFNN) with 6 input schemes in each model, an ensemble was carried out.

The Ensemble method used in this study is a. simple average, b. trimmed average c. variance-based method.

In each ensemble method, 7 individual model schemes are used. Individual model scheme 1 uses 6 individual LSTM models with 6 types of input schemes. Individual model scheme 2 uses 6 individual ELM models with 6 types of input schemes. Individual model scheme 3 uses 6 individual FFNN models with 6 types of input schemes. Individual model scheme 4 uses 6 individual LSTM models with 6 types of input schemes and 6 individual ELM models with 6 types of input schemes. Individual model scheme 5 uses 6 individual LSTM models with 6 types of input schemes and 6 individual FFNN models with 6 types of input schemes.

Individual model scheme 6 uses 6 individual ELM models with 6 types of input schemes and 6 individual FFNN models with 6 types of input schemes. The individual model scheme 7 uses 6 individual LSTM models with 6 kinds of input schemes and 6 individual ELM models with 6 kinds of input schemes and 6 individual FFNN models with 6 kinds of input schemes. The RMSE of the seven individual model schemes for each ensemble method is presented in Table 5.

Table 5. RMSE of ensemble results on training data and testing data

No	Individual Models Used in Ensembles	RMSE					
		Simple average		*Trimmed average*		*Variance-based*	
		Training Data	Testing Data	Training Data	Testing Data	Training Data	Testing Data
1	LSTM with input scheme 1 LSTM with input scheme 2 LSTM with input scheme 3 LSTM with input scheme 4 LSTM with input scheme 5 LSTM with input scheme 6	0.075	0.209	0.076	0.186	0.068	0.105
2	ELM with input scheme 1 ELM with input scheme 2 ELM with input scheme 3 ELM with input scheme 4 ELM with input scheme 5 ELM with input scheme 6	0.744	1.003	0.703	0.612	0.068	0.148
3	FFNN with input scheme 1 FFNN with input scheme 2 FFNN with input scheme 3 FFNN with input scheme 4 FFNN with input scheme 5 FFNN with input scheme 6	0.073	0.168	0.069	0.173	0.051	0.187
4	LSTM with input scheme 1 LSTM with input scheme 2 LSTM with input scheme 3 LSTM with input scheme 4 LSTM with input scheme 5 LSTM with input scheme 6 ELM with input scheme 1 ELM with input scheme 2 ELM with input scheme 3 ELM with input scheme 4 ELM with input scheme 5 ELM with input scheme 6	0.233	0.350	0.226	0.233	0.056	0.094
5	LSTM with input scheme 1 LSTM with input scheme 2 LSTM with input scheme 3 LSTM with input scheme 4 LSTM with input scheme 5 LSTM with input scheme 6 FFNN with input scheme 1 FFNN with input scheme 2 FFNN with input scheme 3 FFNN with input scheme 4 FFNN with input scheme 5 FFNN with input scheme 6	0.072	0.177	0.071	0.171	0.052	0.115

No	Individual Models Used in Ensembles	RMSE					
		Simple average		*Trimmed average*		*Variance-based*	
		Training Data	Testing Data	Training Data	Testing Data	Training Data	Testing Data
6	ELM with input scheme 1 ELM with input scheme 2 ELM with input scheme 3 ELM with input scheme 4 ELM with input scheme 5 ELM with input scheme 6 FFNN with input scheme 1 FFNN with input scheme 2 FFNN with input scheme 3 FFNN with input scheme 4 FFNN with input scheme 5 FFNN with input scheme 6	0.233	0.405	0.225	0.275	0.042	0.091
7	LSTM with input scheme 1 LSTM with input scheme 2 LSTM with input scheme 3 LSTM with input scheme 4 LSTM with input scheme 5 LSTM with input scheme 6 ELM with input scheme 1 ELM with input scheme 2 ELM with input scheme 3 ELM with input scheme 4 ELM with input scheme 5 ELM with input scheme 6 FFNN with input scheme 1 FFNN with input scheme 2 FFNN with input scheme 3 FFNN with input scheme 4 FFNN with input scheme 5 FFNN with input scheme 6	0.140	0.261	0.137	0.194	0.042	0.082

Based on Table 5 the best ensemble method for inflation modeling in Indonesia is the variance-based method compared to simple average and trimmed average. This can be seen from the RMSE value which is almost always the smallest compared to the simple average and trimmed average methods in various individual model schemes.

With the variance-based method, 18 individual models, namely the LSTM model, the ELM model and the FFNN model with each model using 6 different types of inputs have the smallest RMSE among the other 6 individual model schemes. Furthermore, the inflation forecast plot based on the ensemble with the variance-based method with 7 individual model schemes is presented in Figure 6.

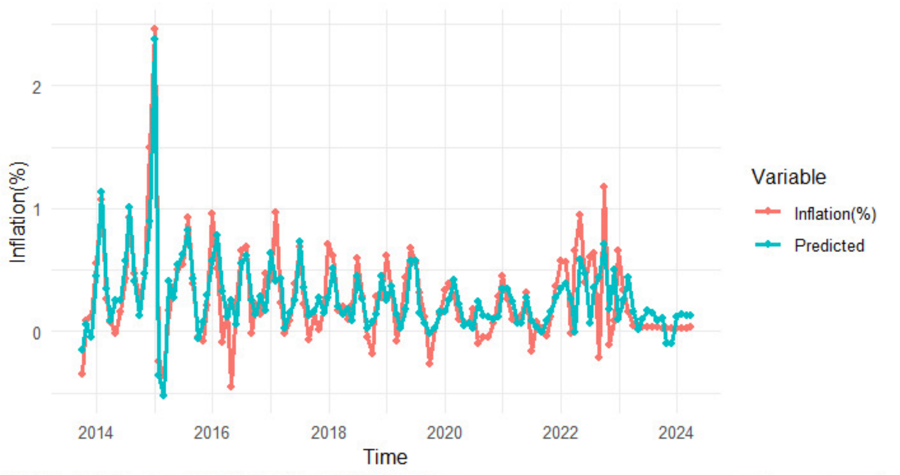

Figure 6. Plot of Indonesian inflation forecast based on the best model

Based on Figure 6, it is evident that the variance-based ensemble method, comprising 18 individual models, yields satisfactory forecasting results for Indonesian inflation. In the early period, it can even capture a fairly high increase in inflation. However, in the concluding period, the model demonstrates a diminished capacity to capture the actual inflation trends.

4. Discussion

The study used 3 individual models, namely the LSTM, ELM and FFNN models. Among the three individual models evaluated, the Feed Forward Neural Network (FFNN) emerged as the most effective. The optimal configuration utilized inputs comprising Indonesian inflation lags (1, 2, and 5), money supply, interest rates, and indicator variables for Eid al-Fitr and government policy. Structurally, the model employed a single hidden layer with 15 neurons and a sigmoid activation function. FFNN is better than LSTM because the data only consists of 132 observations which may be too few for LSTM. LSTM also tends to be susceptible to overfitting if the dataset is limited due to the large number of parameters. FFNN is also better than ELM because the weights in FFNN are optimized during training, not randomly initialized.

The best ensemble method for modeling Indonesian inflation is the variance-based method with RMSE for training data of 0.042 and for testing data of 0.082. This performance is much smaller than the RMSE for the best model, namely FFNN with RMSE for training data of 0.360 and for testing data of 0.270. This shows that combining several models can produce more stable predictions.

5. Conclusion

The research concludes that the variance-based ensemble method serves as the superior approach for forecasting Indonesian inflation. This ensemble is comprised of 18 individual models, utilizing LSTM, ELM, and FFNN architectures, each applied across six distinct input configurations. However, it should be underlined that at the end of the period, this ensemble model still cannot capture the inflation pattern well. Practically, the results of this study provide important implications for policy makers, particularly in supporting the formulation of monetary policy and inflation control strategies. Limitations of this study include the limited variety of model architectures used and the scope of input variables, which could be expanded. Future research could develop an adaptive ensemble weighting scheme to improve the model's ability to withstand periods of high volatility. Furthermore, testing on cross-country data or crisis periods could provide a more comprehensive understanding of the robustness of ensemble methods in inflation forecasting.

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