Long Short Term Memory to Model Indonesian Inflation

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Abstract **– Inflation is a disease-like economic condition that affects nearly every country worldwide. High inflation rates indicate that a country's economic condition is less than ideal. Therefore, controlling inflation is crucial for maintaining a healthy and robust national economy. To control inflation it is necessary to forecast accurate inflation. The modeling for forecasting inflation is quite complex if it is done using existing statistical models because there are many predictor variables that influence inflation. A better approach to use is a machine learning approach. Long Short Term Memory (LSTM) is a machine learning approach capable of producing the best model for inflation forecasting. Therefore, in this study, LSTM will be used as a method to model inflation forecasting. The added value of this study lies in using a comprehensive variable or indicator that determines inflation, so that before modeling using the LSTM, data exploration will be carried out first to determine the indicators that affect inflation. To determine the input, economic theory is used which is supported by statistical analysis, namely correlation analysis and partial autocorrelation function (PACF) statistics. In this research, five input designs were tried. The most optimal LSTM model in predicting inflation in Indonesia is a model that utilizes input variables in the form of Indonesian inflation at lags 2 and 4, the CNY, EUR, and USD exchange rates, interest rates, Eid al-Fitr indicators, government policy indicators, and world oil prices.**

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1. Introduction

Bank Indonesia defines inflation as a widespread and sustained tendency for prices to rise. Inflation is a common economic problem in almost every country worldwide. High inflation indicates a country's economic health. Therefore, inflation needs to be controlled to maintain a stable and resilient economy.

Inflation is caused by many factors. The first cause of inflation is increased demand (Demand Pull Inflation). Increased demand usually occurs because of a celebration, for example the celebration of a religious holiday. The majority of Indonesia's population is Muslim and celebrates Eid al-Fitr. In the months of Eid al-Fitr the demand for goods or services increases and this causes an increase in inflation. Several studies such as [1], [2] prove that Eid al-Fitr has a positive effect on inflation, meaning that Eid al-Fitr can increase inflation in Indonesia. Meanwhile, an increase in interest rates can reduce public demand because people will be more interested in saving than spending which causes inflation tofall. The research by [3], [4] is discussing the effect of interest rates on inflation. The second cause of inflation is the money supply (Quantity Theory of Inflation). When the money supply increases while the amount of goods remains the same, the price of goods tends to rise. Several studies conducted by [1], [4], [5], [6], [7] have analyzed the effect of the money supply on the inflation rate in various countries. The increase in production costs (Cost Push Inflation) is the third cause of inflation. Increases in production costs within a certain period of time will continuously increase inflation. The increase in production costs can be caused by rising foreign exchange rates so that raw materials from abroad become expensive. This has been studied by [8], [9] and [10]. Changes in exchange rates for crypto currencies such as bitcoin can also affect inflation [11]. In addition, inflation of another country, especially countries that are trading partners, will also cause raw materials from abroad to become more expensive.

Other causes of inflation related to increasing production costs include increases in world oil prices, increases in fuel prices, and increases in basic electricity tariffs as mentioned in [12] and [13].

This research aims to identify important indicators or variables in forming models for forecasting inflation. The second objective is to form an accurate model for forecasting inflation.

Modeling for forecasting inflation is quite complex if done using existing statistical models because there are many predictor variables that influence inflation. Another approach that is better to use is a machine learning approach. The study in [14] indicates that the machine learning approach provides better results than the time series method in forecasting inflation in the United States. Meanwhile, the study [15] compares several machine learning techniques, namely Long Short Term Memory (LSTM) networks, K–Nearest Neighbors, extreme gradient boosting and random forest in the context of inflation forecasting. This research shows that LSTM produces the best model for forecasting inflation in Costa Rica. Research by [16] also shows the use of LSTM for inflation forecasting and producing accurate models. These findings indicate that Long Short Term Memory (LSTM) is one of the most effective machine learning approaches in predicting inflation. However, previous research did not precede the model building process by exploring data to determine indicators or variables that influence inflation. In this research, statistical methods such as correlation analysis will be used to determine the variables that will be used as input for forecasting inflation. This study also applies the partial autocorrelation function (PACF) as a statistical tool to determine the inflation lag value to be included in the LSTM model. Previous research also did not use comprehensive input. Some studies only used inflation in the previous period as an input. Other studies used variables other than inflation in the previous period but only domestic effects and do not consider world conditions. This research considers all aspects that influence inflation, including previous period inflation, other variables that influence inflation such as the money supply and interest rates as well as world conditions such as world oil prices, inflation in other countries and the IDR exchange rate against other countries' currencies that has trade relations with Indonesia and the price of bitcoin. Apart from that, Indonesia's characteristics, namely increasing inflation around Eid al-Fitr, are also considered as input, as are government policies that cause inflation to rise, such as increases in fuel prices.

2. Methodology

Data on inflation, money supply, and interest rates were obtained from [17], while inflation data for China, the United States, the European Union, and Bitcoin prices were obtained from [18], [19], [20], and [21] respectively. The rupiah exchange rate (IDR) was obtained from [22] and global oil price data was obtained from [23]. All data used is monthly from April 2013 to January 2023. This data is then scaled using a min – max scale with the formula:

$$y_{new} = \frac{y_{old} - min}{max - min} \quad (1)$$

Before modeling with LSTM, the data is separated into two sets, namely 80 percent for training and 20 percent for testing.

2.1. Long Short Term Memory (LSTM)

Long Short Term Memory (LSTM) is a machine learning method designed to handle time series data. Long Short Term Memory or LSTM was first introduced by [24] and has been widely used in [25], and [26]. The LSTM structure includes a memory cell, a forget gate, an input gate, and an output gate. The memory cell plays a role in storing long-term information, while the input and output gates regulate the flow of information into and out of the memory cell. The first process begins by calculating the output value from the previous time and the value at the current time. These two values are then used as input to calculate the forget gate and the input gate. The next step is to perform calculations on the forget gate and the input gate using a specific formula:

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

Calculations at the input gate using the equation:

$$i_t = \sigma(W_i.[l_{t-1}, y_t] + b_i) \quad (3)$$
$$C_t' = \tanh(W_c.[l_{t-1}, y_t] + b_c)$$

Where

f_t: forget gate value at time t, with a range of values between 0 and 1

i_t: input gate value at time t, with a range of values between 0 and 1

C_t': candidate cell at the input gate at time t

W_f: weight at the forget gate

W_i: weight at the input gate

W_c: weight for the candidate cell at the input gate

l_{t-1}: output value of the process at the previous time

y_t: input value at time t

b_f: bias value applied to the forget gate

b_i: bias value applied to the input gate

b_c: bias value applied to the candidate cell at the input gate

Tanh: Hyperbolic tan activation function with a function using the equation (4):

$$f(y) = \frac{\exp(2y) - 1}{\exp(2y) + 1} \quad (4)$$

σ: sigmoid activation function with a function using the equation (5)

$$f(y) = \frac{1}{1 + exp(-y)} \quad (5)$$

The next step is to adjust the cell values or model parameters. The formula for the calculation in this step is:

$$C_t = f_t \times C_{t-1} + i_t \times C_t' \quad (6)$$

The output value is obtained from:

$$O_t = \sigma(W_o [l_{t-1}, y_t] + b_o) \quad (7)$$

where

O_t : output gate at time t, with a value range between 0 and 1

W_o : weight applied to the output gate

b_o: bias value applied to output gate

The final output value of the output gate is calculated using a formula:

$$l_t = O_t \times \tanh(C_t) \quad (8)$$

where

l_t: the final output value of the LSTM at the time t by the output gate.

After obtaining several LSTM models from several inputs, the next step is to select the best model using the smallest MAPE (Mean Absolute Percentage Error) criteria. According to [27] the MAPE formula is:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \times 100\% \quad (9)$$

Input determination is important in LSTM modeling. In the LSTM model, the lag of a variable can be used as one of the inputs. To determine the relevant lag, the Partial Autocorrelation Function (PACF) method is used. The selection of other input variables is based on the correlation between the variables.

2.2. Partial Autocorrelation Function

Partial Autocorrelation Function (PACF) denoted by ϕ_{kk} measures the correlation between Y_t and Y_{t+k} after the influence of the linear relationship from Y_t to $Y_{t+1}, Y_{t+2}, \ldots, Y_{t+k-1}$ is removed. According to [20] PACF can be calculated in stages, starting from $\hat{\phi}_{11} = \hat{\rho}_1$ and the value of $\hat{\phi}_{kk}$ is then obtained through the following formula:

$$\hat{\phi}_{k+1,k+1} = \frac{\hat{\rho}_{k+1} - \sum_{j=1}^{k}\hat{\phi}_{kj}\hat{\rho}_{k+1-j}}{1 - \sum_{j=1}^{k}\hat{\phi}_{kj}\hat{\rho}_j} \quad (10)$$

and

$$\hat{\phi}_{k+1,j} = \hat{\phi}_{kj} - \hat{\phi}_{k+1,k+1}\hat{\phi}_{k,k+1-j}, \quad j = 1, 2, \ldots, k \quad (11)$$

where

$$\hat{\rho}_k = \frac{\sum_{t=1}^{n-k}(Y_t - \bar{Y})(Y_{t+k} - \bar{Y})}{\sum_{t=1}^{n}(Y_t - \bar{Y})^2}, \quad (12)$$

$$k = 0, 1, 2, \ldots$$

2.3. Correlation

Correlation is a statistical measure used to assess the degree of closeness of the relationship between two variables. The correlation coefficient has a value between -1 and 1. A value closer to -1 indicates a strong negative relationship; a value closer to 1 indicates a strong positive relationship. Meanwhile, a coefficient value closer to zero indicates no relationship between the two variables. The correlation coefficient can be calculated using the following equation.

$$r_{XY} = \frac{n\sum_{i=1}^{n}X_iY_i - \sum_{i=1}^{n}X_i\sum_{i=1}^{n}Y_i}{\sqrt{n\sum_{i=1}^{n}X_i^2 - \left(\sum_{i=1}^{n}X_i\right)^2}\sqrt{n\sum_{i=1}^{n}Y_i^2 - \left(\sum_{i=1}^{n}} \quad (13)$$

3. Results

Analysis of time series data begins with plotting time series data for exploration. Data plots are used to determine the characteristics and patterns contained in the data. The time series data plot is presented in Figure 1.

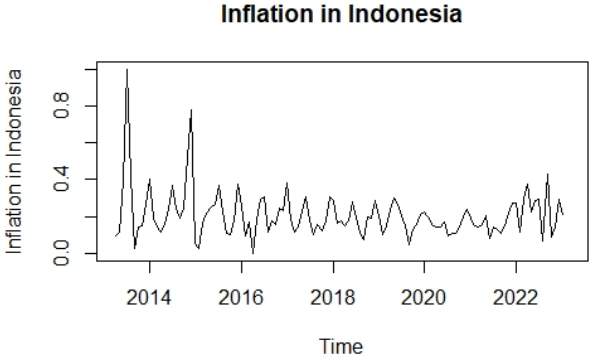

Figure 1. Plot of inflation of Indonesia

Figure 1 shows a pattern that tends to be flat, with several periods of prominent inflation, namely in July 2013 and December 2014. The increase in inflation in July 2013 was caused by the increase in fuel prices that occurred in June 2013.

Similarly, high inflation in December 2014 was related to the increase in fuel prices in November 2014. To determine the lag of Indonesian inflation that will be used as input, Partial Autocorrelation Function (PACF) analysis is used as shown in Figure 2.

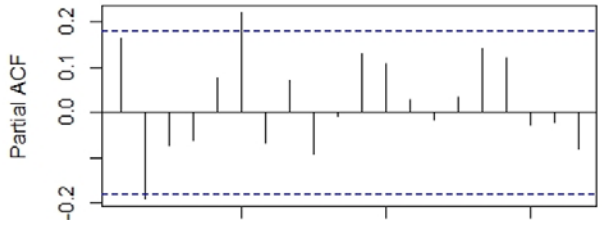

Figure 2. Plot of partial autocorrelation function of Indonesian inflation

Based on Figure 2, the lags that show significance are lag 2 and lag 4, so both are selected as input for the analysis. In theory, inflation in Indonesia is also influenced by inflation in countries that have trade relations with Indonesia. The relationship between inflation in Indonesia and inflation in China, the European Union and the United Kingdom is presented in Figure 3.

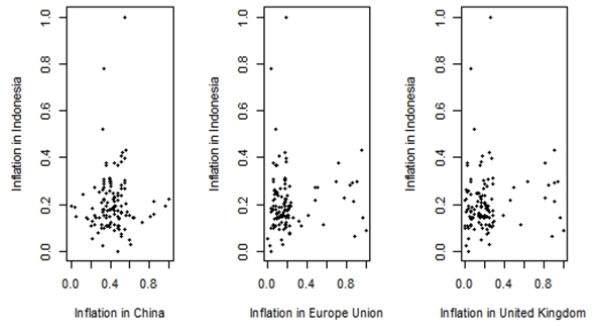

Figure 3. Plot Indonesian inflation vs other country's inflation

Figure 3 shows that inflation in Indonesia is not related to inflation in China, the European Union, or the United Kingdom. This is also reflected in the correlation coefficient between Indonesian inflation and inflation in the European Union and the United Kingdom, presented in Table 1.

Table 1. Correlation coefficient between inflation in Indonesia and input candidates

Correlation Coefficient	**Inflation in Indonesia**
China's Inflation Rate	0.0505 (0.5866)
European inflation rate	0.0623 (0.5028)
United Kingdom Inflation rate	0.0899 (0.3326)
Exchange rate of CNY	-0.2037 (0.0269)
Exchange rate of EUR	-0.2370 (0.0097)
Exchange rate of USD	-0.2582 (0.0047)
Exchange rate of GBP	-0.1482 (0.1092)
Money supply	-0.1519 (0.1004)
Interest rate	0.1826 (0.04775)
Bitcoin price (USD)	-0.0910 (0.3266)
Eid al-Fitr indicator	0.1883 (0.0411)
Government policy indicator	0.1807 (0.0502)
World oil price	0.2407 (0.0087)

The table shows that the correlation between Indonesian inflation and inflation in China, the European Union, and the United Kingdom is very low, at less than 0.1. Furthermore, inflation in Indonesia is also influenced by the rupiah exchange rate against the currencies of its trading partners. The relationship between Indonesian inflation and the exchange rates of the Chinese and European Union currencies is shown in Figure 4. while the relationship with the US dollar (USD) and British pound sterling (GBP) exchange rates is presented in Figure 5.

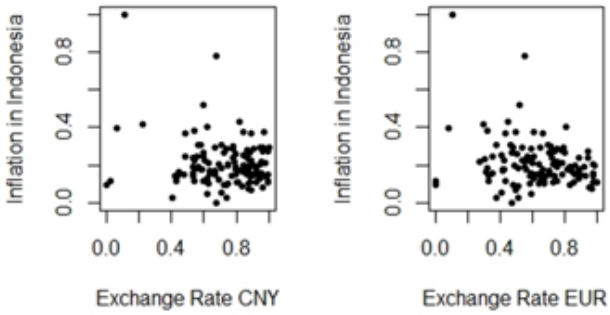

Figure 4. Plot of inflation in Indonesia vs exchange rate of CNY and exchange rate of EUR

Based on Figure 4, it can be concluded that inflation is related to the exchange rates of Chinese and European Union currencies, although the level of correlation is low. This can be seen from the correlation coefficient between inflation in Indonesia and Exchange Rate of CNY and Exchange Rate of EUR of -0.2036504 and - 0.2370358 respectively. This information is presented in Table 1.

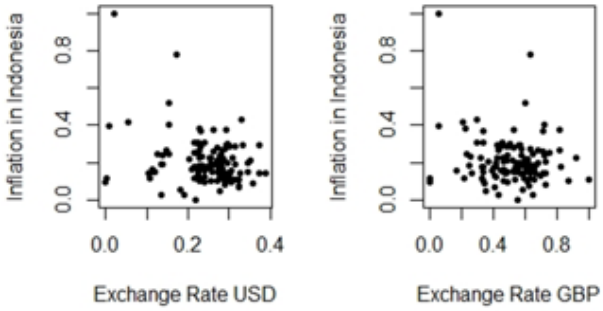

Figure 5. Plot of inflation in Indonesia vs exchange rate of USD and exchange rate of GBP

Meanwhile, Figure 5 shows that inflation in Indonesia has a low correlation with the US dollar and British pound exchange rates. This can be shown from the correlation coefficient between inflation in Indonesia and the US exchange rate and the UK exchange rate of -0.2582864 and -0.1482106 respectively. Furthermore, the relationship between inflation in Indonesia and other candidate inputs, namely money supply, interest rate and bitcoin price, is presented in Figure 6. Only the interest rate of the three variables, shows a relationship with inflation in Indonesia, although weak.

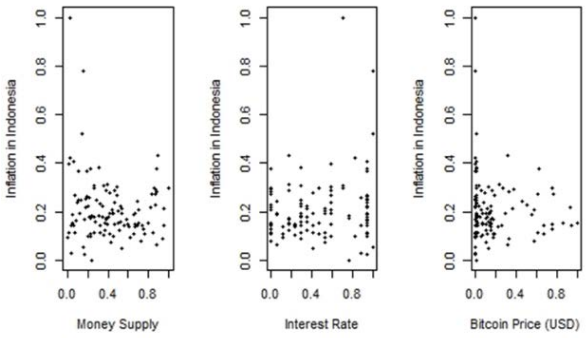

Figure 6. Plot of inflation in Indonesia vs money supply, interest rate and Bitcoin price

Based on the various analyzes that have been carried out, the input for modeling inflation forecasting is designed using the LSTM. The design is presented in Table 2.

Table 2. Input design

No.	Output	Input
1.	Inflation in Indonesia	Inflation in Indonesia lag 2
2.	Inflation in Indonesia	Inflation in Indonesia lag 6
3.	Inflation in Indonesia	Inflation in Indonesia lag 2, inflation in Indonesia lag 6
4.	Inflation in Indonesia	Inflation in Indonesia lag 2, inflation in Indonesia lag 6, Chinese Yuan Exchange Rate, EUR exchange rate, USD exchange rate, interest rate, Eid al-Fitr indicator, government policy indicator, world oil price
5.	Inflation in Indonesia	Inflation in Indonesia lag 2, inflation in Indonesia lag 6, inflation in China, inflation in Europe, inflation in UK, Chinese Yuan Exchange Rate, EUR exchange rate, USD exchange rate, GBP exchange rate, money supply, interest rate, bitcoin price, Eid al-Fitr indicator, government policy indicator, world oil price

Because the significant PACF is the PACF at lag 2 and lag 6, the input tested in design 1 is inflation in Indonesia lag 2, the input tested in design 2 is inflation in Indonesian lag 6 and the input tested in design 3 is inflation in Indonesia lag 2 and lag 6.

Based on PACF and correlation analysis, then in design 4 used were the inputs inflation in Indonesia lag 2, inflation in Indonesia lag 6 and variables that are correlated with inflation in Indonesia, namely the Chinese Yuan Exchange Rate, EUR exchange rate, USD exchange rate, GBP exchange rate, interest rates, Eid al-Fitr indicators and government policy indicator government and world oil prices.

Next, design 5 tries to use all variables that are thought to influence inflation in Indonesia even though not related in correlation analysis.

Furthermore, the data that has been obtained is separated into two sets, namely 80 percent for training and 20 percent for testing. Then do the scaling using the max – min transformation. The weight estimation using the adam optimizer and the MAPE calculation results are presented in Table 3.

Table 3. MAPE for model of inflation in Indonesia using LSTM with various input

No	Input	MAPE
1.	Inflation in Indonesia Lag 2	2.9848
2.	Inflation in Indonesia Lag 6	2.5792
3.	Inflation in Indonesia Lag 2, Inflation in Indonesia lag 6	2.7335
4.	Inflation in Indonesia lag 2, inflation in Indonesia lag 6, Chinese Yuan Exchange Rate, EUR exchange rate, USD exchange rate, interest rate, Eid al-Fitr indicator, government policy indicator, world oil price	1.6876
5.	Inflation in Indonesia lag 2, inflation in Indonesia lag 6, inflation in China, inflation in Europe, inflation in UK, Chinese Yuan Exchange Rate, EUR exchange rate, USD exchange rate, GBP exchange rate, money supply, interest rate, bitcoin price, Eid al-Fitr indicator, government policy indicator, world oil price	2.0339

Table 3 shows that the model of inflation in Indonesia using LSTM with input according to design 4 has the smallest MAPE. This shows that the model with design 4 is the best model. This also shows that the correlation analysis and partial autocorrelation function statistic are very helpful in selecting inputs to obtain the best model. These results are consistent with research conducted by [28] which says that choosing the right input will determine forecasting accuracy [28].

Table 4. Actual and prediction data

No.	Actual Data	Prediction Data using LSTM
1.	0.08	0.1602
2.	0.13	0.1636
3.	0.32	0.2712
4.	-0.16	0.1803
5.	0.08	0.1746
6.	0.03	0.1902
7.	-0.04	0.1769
8.	0.12	0.2012
9.	0.37	0.2004
10.	0.57	0.1831
11.	0.56	0.1896
12.	-0.02	0.1854
13.	0.66	0.1985
14.	0.95	0.2133
15.	0.4	0.2853
16.	0.61	0.1883
17.	0.64	0.1893
18.	-0.21	0.1656
19.	1.17	0.2296
20.	-0.11	0.2220
21.	0.09	0.1624
22.	0.66	0.2462
23.	0.34	0.2120

Furthermore, the prediction results on data testing using the LSTM model with input in design 4 are presented in Table 4 and presented in graphical form in Figure 7.

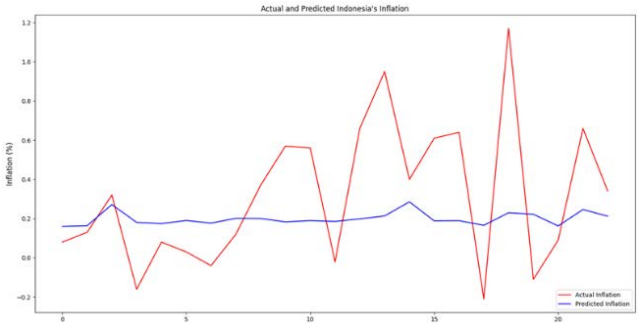

Figure 7. Plot of actual data vs predicton data

Figure 7 shows that the prediction data tends to be horizontal only. However, at several points when there was an increase in the actual data, the predicted data also rose but were unable to approach a high enough increase.

To further assess the predictive accuracy, error metrics were computed. The model achieved a Mean Absolute Error (MAE) of 0.18, a Mean Squared Error (MSE) of 0.05, and a Root Mean Squared Error (RMSE) of 0.22, indicating that the model explains only a small portion of the variance in the actual data.

These results suggest that while the LSTM model is able to follow the general direction of the trend, its ability to capture large fluctuations remains limited.

4. Discussion

In time series modeling, the predictor or input variable that is often used is the lag of the variable in question. In statistics, to determine which lag is used as a predictor, a tool called the partial autocorrelation function (PACF) is used. Thus, in this study, PACF is utilized to identify the lags that will be used as input to the LSTM model. Figure 2 shows that the significant lags are lag 2 and lag 6, so three input schemes were tried that use inflation lag, namely scheme 1 uses lag 2 inflation as input. Scheme 2 uses lag 6 inflation as input and scheme 3 uses lag 2 and lag 6 inflation as input. In addition to inflation lag, inputs that need to be considered in this LSTM modeling are variables that economically affect inflation. Economic factors that influence inflation include inflation in countries with which Indonesia has trade relations, exchange rates from other countries that have trade relations with Indonesia, interest rates, world oil prices, bitcoin prices, money supply and fuel price increases. In addition, Indonesia has special characteristics related to the Eid al-Fitr holiday. During the Eid celebration, Indonesian people's spending will increase because of buying a lot of goods, food, and fuel as well. This usually triggers an increase in inflation. To select the variables that will be used as input, a statistical tool is used, namely correlation analysis. Therefore, in scheme 4, the inputs used are inflation lag 2 and inflation lag 6 (significant inflation lag based on PACF) and variables that are statistically significantly correlated with inflation. While scheme 5 tries to use all variables that are suspected of influencing inflation as input even though not statistically significantly correlated with inflation.

Table 3 shows that LSTM with input scheme 4 produces the best performance. In scheme 4, the input used is significant inflation lag based on PACF analysis and variables that are statistically significantly correlated with inflation. This shows the importance of statistical analysis such as correlation analysis and PACF analysis in selecting input for LSTM. Scheme 5, which uses all variables suspected of influencing inflation, has the second smallest MAPE. While schemes 1, 2 and 3, which only use inflation lag, have larger MAPE. This shows that it is not enough to just use the lag of inflation as input in LSTM modeling, but it is also necessary to consider variables that economically also affect inflation. Knowledge of the variables that affect inflation is also very important in selecting input.

5. Conclusion

Inflation modeling in Indonesia is quite complex because of the spatio-temporal relationship to inflation and the influence of other variables, both from within and from abroad. In addition, the unique characteristics of inflation in Indonesia, such as the Eid al-Fitr effect, also play a role in modeling inflation in Indonesia. Input selection in LSTM is important to determine accuracy. Determining input can be assisted by statistical analysis, namely correlation analysis and partial autocorrelation function (PACF) statistics. This study found that the most accurate prediction of Indonesian inflation was obtained through the LSTM model, combining inputs such as lags of Indonesian inflation in periods 2 and 4, the CNY, EUR, and USD exchange rates, interest rates, and indicators for Eid al-Fitr celebrations, government policy indicators and world oil prices. These inputs are selected based on economic theory and supported by correlation analysis and PACF statistics. LSTM models with more inputs that are not statistically significantly related to Indonesian inflation do not produce the best model. An important finding in this study is that to select inputs in inflation modeling using LSTM, it is important to know the variables that influence inflation economically and the characteristics of a country and then test them using statistical tools, namely correlation analysis and PACF. This should be addressed in further research.

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