Jurnal CoreIT, Vol.10, No.2, Dec 2024
ISSN 2460-738X (Print)
ISSN 2599-3321 (Online)

An Analysis And Forecasting The Foodstuffs Prices In Surabaya Traditional Market Using LSTM

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Abstract. Food is one of the essential things in society. Foodstuffs prices are important factors in the stability economy. In Indonesian society, some foodstuffs, e.g., rice, beef, chicken egg, cooking oil, and sugar are the main ingredients in their cuisine. Analyzing and predicting the foodstuffs price is interesting job. This research is conducted to develop models for forecasting the price of rice, beef, chicken egg, cooking oil, and sugar. It implements the Long Short-Term Memory (LSTM) model and a daily time-series dataset from a traditional market in Surabaya. Surabaya is the capital city of East Java province, and it is one of the densest cities in Indonesia. The experiments run univariate time-series forecasting. The experimental results show that LSTM works well to forecast the price of rice, beef, chicken egg, cooking oil, and sugar. The evaluation results obtain MAPE scores as 0.12%, 0.03%, 0.72%, 0.36%, and 0.08% for models of rice, beef, chicken egg, cooking oil, and sugar, respectively. The annual average price of beef, chicken egg, and cooking oil show an increasing trend and those foodstuffs have positive correlations with each other.

Keywords: LSTM, forecasting, price, foodstuff, RNN.

Received Dec 2023 / **Revised** November 2024 / **Accepted** Des 2024

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INTRODUCTION

Foodstuff is a substance with food value and it is the material to make food. The essential foodstuffs might be different in one and another place. Foodstuffs prices play an important role in the economic. A study reveals the unidirectional causality between global food price to food price inflation [1]. The global pandemic Covid-19 also impacts food prices [2]. A study in Kenya found there was unidirectional Granger causality from diesel prices to cabbage and potatoes prices [3].

Some research has been done to analyze the models fit for forecasting the prices of foodstuffs. Autoregressive Integrated Moving Average (ARIMA) has been implemented to forecast food prices [4] [5] [6] [7]. A model for rice price forecasting using Adaptive Neuro-Fuzzy Inference System (ANFIS) produces a Mean Absolute Percentage Error (MAPE) of 0.70059% [8]. Extreme Learning Machine (ELM) for forecasting the staple food price obtains an accuracy of 98.79% [9]. Backpropagation Neural Networks (BPNN) have successfully to be implemented for forecasting the price of agricultural product [10]. Gated recurrent units (GRUs) produce a higher accuracy in forecasting the daily price of chicken egg, rice, and broiler meat [11].

Rice, cooking oil, and sugar are mandatory foodstuffs in Indonesian households. Rice is the main food for most Indonesian [12]. They eat rice three times a day. Fried rice is a popular Indonesian cuisine made from rice and it usually eat with fried egg. Cooking oil is also an important part of Indonesian cuisine. Fried food or in the Indonesian language is named gorengan, made by deep fried. Fried food is one of the most popular street food in Indonesia. Fried food sellers are always everywhere. It indicates the consumption of cooking oil is high. Beef is one of the most well-known main ingredients in Indonesian food, e.g., rendang, satay, soto, and meatball [12]. Many Indonesian loves sweet food and drink. Therefore, sugar is another important foodstuff. It is common that Indonesian to put sugar in their beverages. Wedang is one of the sweet beverages made from spices and sugar.

DOI: 10.24014/coreit.v10i2.27855

Surabaya is the capital city of East Java province. It is one of the most densely populated cities in Indonesia. In 2020, the population in Surabaya is 2,904,751 [13]. Surabaya has a tropical climate and there are two seasons: wet and dry season. Analyzing and forecasting the price of foodstuffs is beneficial to produce information for the government and society to control food stability.

The goal of this research is to find the best model for forecasting the prices of foodstuffs, i.e., rice, beef, chicken egg, cooking oil, and sugar. It proposes to use Long Short-Term Memory (LSTM) model for univariate time-series forecasting. The advance of this research is to develop an application for forecasting and analyzing the price of rice, beef, chicken egg, cooking oil, and sugar based on the price in Surabaya traditional market.

METHODS

An artificial neural network that employs internal loops is named a recurrent neural network (RNN) [14]. The internal loops move recursive dynamics in the networks and cause delayed activation dependencies

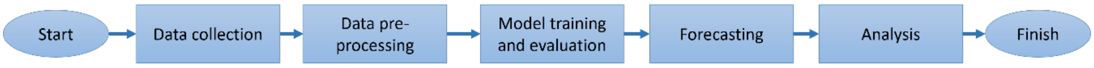

Figure 1 Research workflow.

across the processing elements in the network. RNN is suitable to proceed with the time series and sequence data [15]. Long Short-Term Memory is a specific version of RNN. The architecture of LSTM contains input gate and output gate [16]. The LSTM model is defined by equation (1-7), where $\boldsymbol{c_j}$ is the $\boldsymbol{j}$-th memory cell, $\boldsymbol{w}$ is weight, $\boldsymbol{y^{c_j}(t)}$ is the output of $\boldsymbol{c_j}$ at time $\boldsymbol{t}$, $\boldsymbol{y^{in_j}(t)}$ is activation of $\boldsymbol{in_j}$, and $\boldsymbol{y^{out_j}(t)}$ is activation of $\boldsymbol{out_j}$ at time $\boldsymbol{t}$. LSTM has been implemented for forecasting time-series data. LSTM works well to forecast air pollutants [17] [18] [19] [20] [21]. LSTM is also a powerful model to forecast stock prices [22] [23] [24].

$$y^{out_j}(t) = f_{out_j}\left(net_{out_j}(t)\right) \quad (1)$$

$$y^{in_j}(t) = f_{in_j}\left(net_{in_j}(t)\right) \quad (2)$$

$$net_{out_j}(t) = \sum_u w_{out_j u} y^u(t-1) \quad (3)$$

$$net_{in_j}(t) = \sum_u w_{in_j u} y^u(t-1) \quad (4)$$

$$net_{c_j}(t) = \sum_u w_{c_j u} y^u(t-1) \quad (5)$$

$$y^{c_j}(t) = y^{out_j}(t) h\left(s_{c_j}(t)\right) \quad (6)$$

$$s_{c_j}(0) = 0\,,$$

$$s_{c_j}(t) = s_{c_j}(t-1) + y^{in_j}(t) g\left(net_{c_j}(t)\right) \text{ for } t > 0 \quad (7)$$

The evaluation metrics for forecasting jobs are mean absolute error (MAE), Mean absolute percentage error (MAPE), and mean square error (MSE), and root mean square error (RMSE) [18]. Let $\boldsymbol{s}$, $\boldsymbol{s'}$, and be the true value, the predicted value, and the number of samples. MAE is defined as $\frac{1}{n}\sum_{i=1}^{n}|s_i' - s_i|$ and MAPE can be computed by $\frac{100}{n}\sum_{i=1}^{n}\left|\frac{s_i - s_i'}{s_i}\right|$. MSE is calculated by $\frac{1}{n}\sum_{i=1}^{n}(s - s_i)^2$ and RMSE is $\sqrt{MSE}$.

A research workflow is illustrated in Figure 1. The research workflow contains data collection, data pre-processing, model training and evaluation, forecasting, and analysis. It collects daily time series of foodstuffs prices. Data preprocessing is a phase to manage missing values. The missing data is filled up using the interpolation function. This research implements the LSTM model. The model is trained for forecasting the price of rice, beef, chicken egg, cooking oil, and sugar. The trained model is evaluated using MAPE, MSE, and MAE. The trained model is then used for forecasting these foodstuffs prices. The last step is analyzing the trend of foodstuffs prices.

RESULT AND DISCUSSION

A dataset is collected from Information Center for National Strategic Food Price [25]. The data are recorded from Surabaya traditional market. The dataset is a daily time series containing the price of rice, beef, chicken egg, cooking oil, and sugar from January 2018 - February 2023. Figure 2 shows the prices of rice, beef, chicken egg, cooking oil, and sugar. The price is in Indonesian Rupiah (IDR), the currency used in Indonesia. Rice has a stable price with an average of IDR 11,814. Beef is the most expensive foodstuff among others and it has an average price of IDR 118,068. The price of chicken eggs is fluctuated from IDR 16,500 to IDR 31,000 and the average price is IDR 23,362. Cooking oil price has an increasing trend with an average is around IRD 14,837. The average price of sugar is about IDR 13,470.

This paper implements LSTM from Tensorflow for Python [26]. The dataset is divided into 80% for training and 20% for testing. The experiments are univariate time series forecasting. It runs several scenarios for experiments with changing the values of the unit layer, batch size, time step, optimizer, and learning rate. The experiments use Relu activation functions and run 100 epochs. It uses evaluation metrics MAPE, MSE, and MAE. Figure 3 displays the evaluation of prediction values. The time step and batch size affect the prediction values and the best output is obtained when the time step = 1. There is no significant difference in the error when implementing various optimizers and learning rates. The best LSTM model for forecasting the foodstuff prices is two layers with weights are 64 and 32, respectively. Table 1 shows the best experimental results in forecasting the foodstuffs prices. An optimum model works uniquely for each foodstuff price. The comparison of actual data and prediction is displayed in Figure 4. It shows that LSTM models work well to forecast the price of rice, beef, chicken egg, cooking oil, and sugar. The LSTM-trained models are then used to build an application for foodstuff price prediction. The application is designed for Indonesian speakers.

Figure 5 – 9 show the trend of foodstuffs price in Surabaya traditional market. Figure 5 shows the annual and montly trend of rice price. The rice price has slightly changed. From 2018 - 2022, the average price of rice decreased to around IDR 600. The most expensive rice happened in February and the cheapest one is in August. Beef tends to be more expensive and shows an increasing trend (see Figure 6). From June - December, beef becomes more pricey. In 2021, beef reached the highest price and the monthly trend reveals that the most expensive beef occurs in May. Figure 7 describes the trend in chicken egg prices. The annual average trend shows that chicken egg becomes more expensive. From 2019 – 2022, the maximum price always incresed. The cheapest price occurred in October. The range of minimum and maximum chicken egg prices was almost two times. The trend of cooking oil price is described in Figure 8. The annual trend of cooking oil prices is always rising. The average trend shows that it increases around IDR 7,000. The monthly trend finds that cooking oil is expensive in January, April, and December. The sugar price is displayed in Figure 9. The annual trend of sugar prices is slightly rising at about IDR 2,000. From January - April, the sugar prices increased, and they decreased from May - December. The most expensive price is in April.

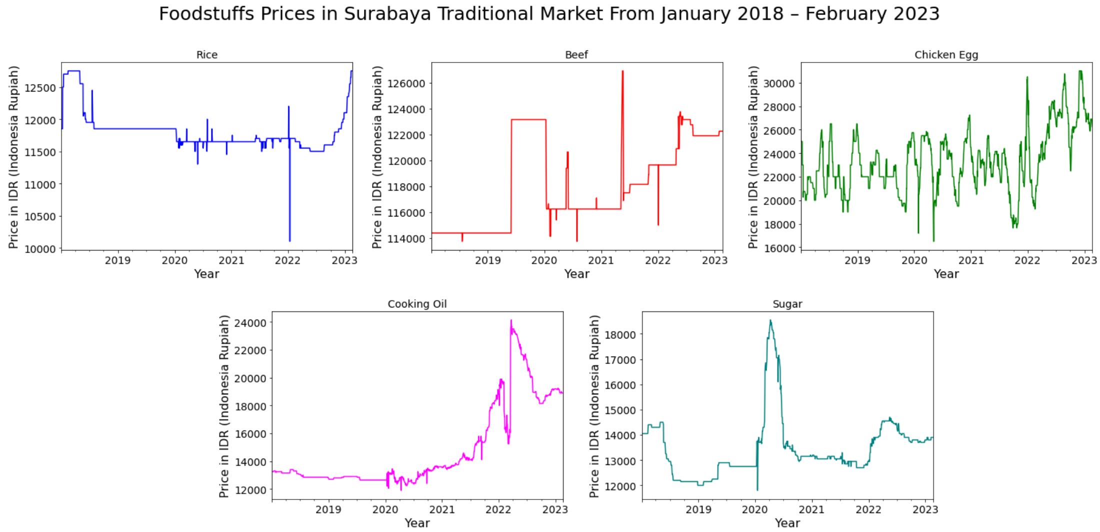

Figure 2 The foodstuffs prices in Surabaya traditional market from Januari 2018 - Februari 2023.

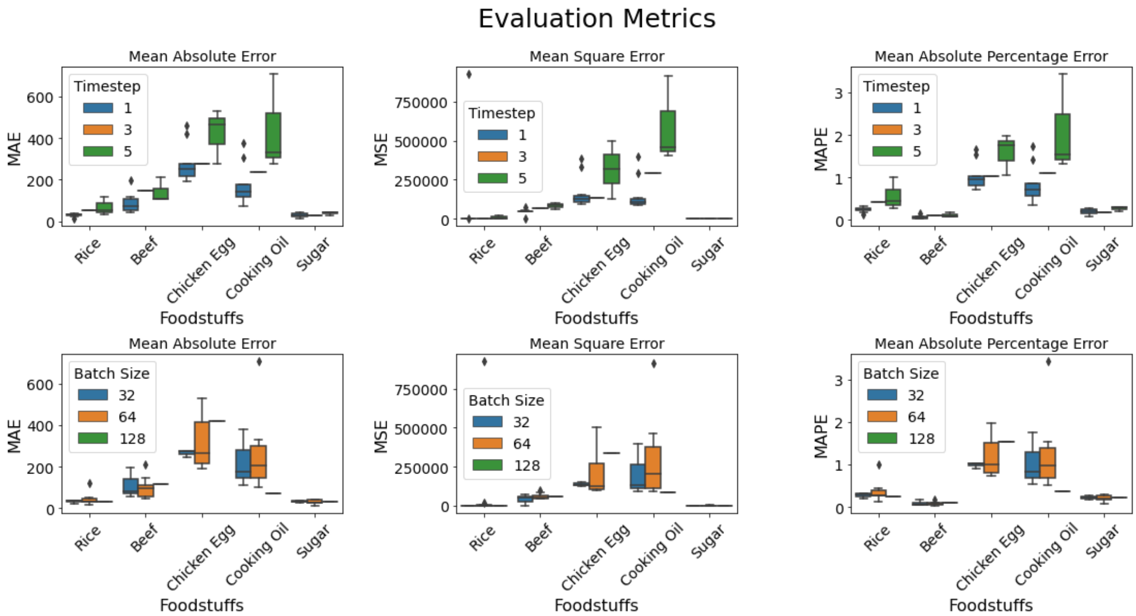

Figure 3 Evaluation metrics

Table 1 The best experimental results

Foodstuffs	Batch Size	Optimizer	MAE	MAPE	MSE	Learning Rate
Rice	64	Adadelta	14.65	0.12%	484.14	1
Beef	64	Adam	43.92	0.03%	45,038.65	0.001
Chicken Egg	64	RMSprop	190.73	0.72%	96,342.92	0.001
Cooking Oil	128	Adam	72.27	0.36%	85,432	0.001
Sugar	64	Nadam	12.38	0.08%	841.11	0.001

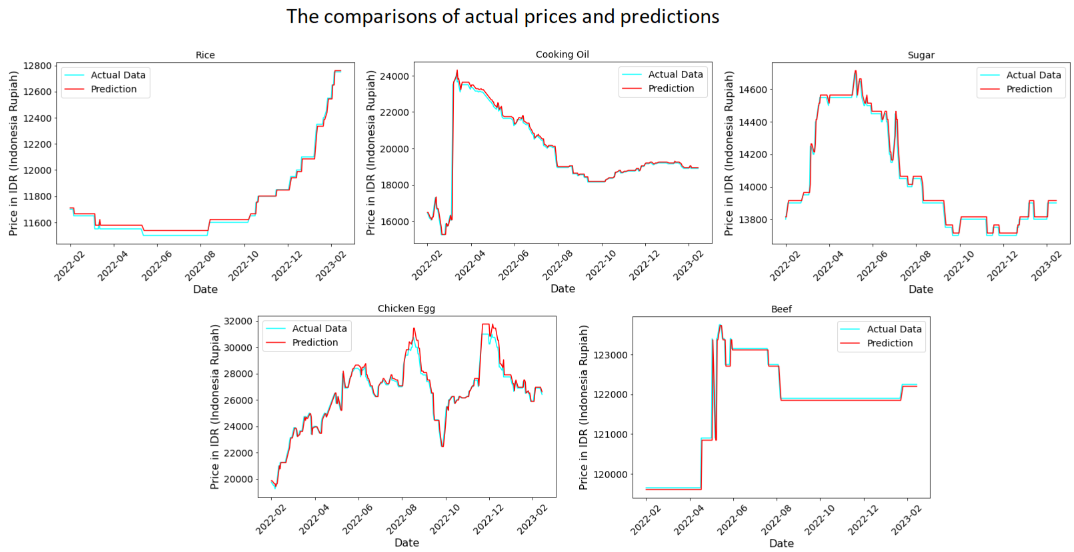

Figure 4 The comparison of actual prices and prediction

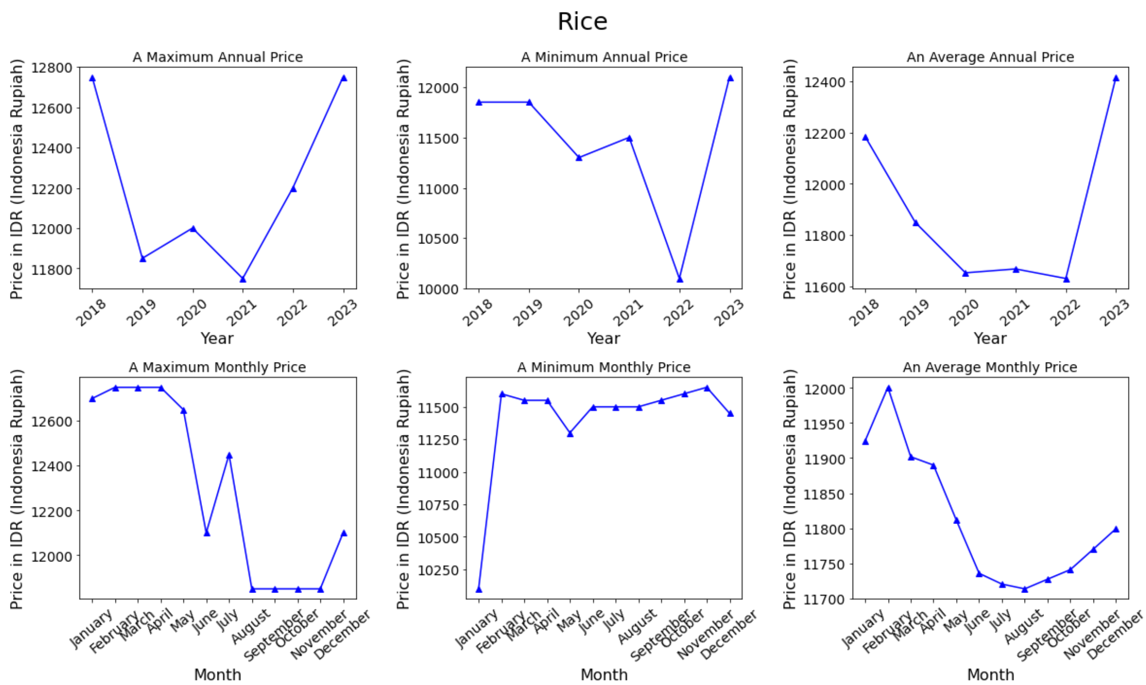

Figure 5 The price of rice

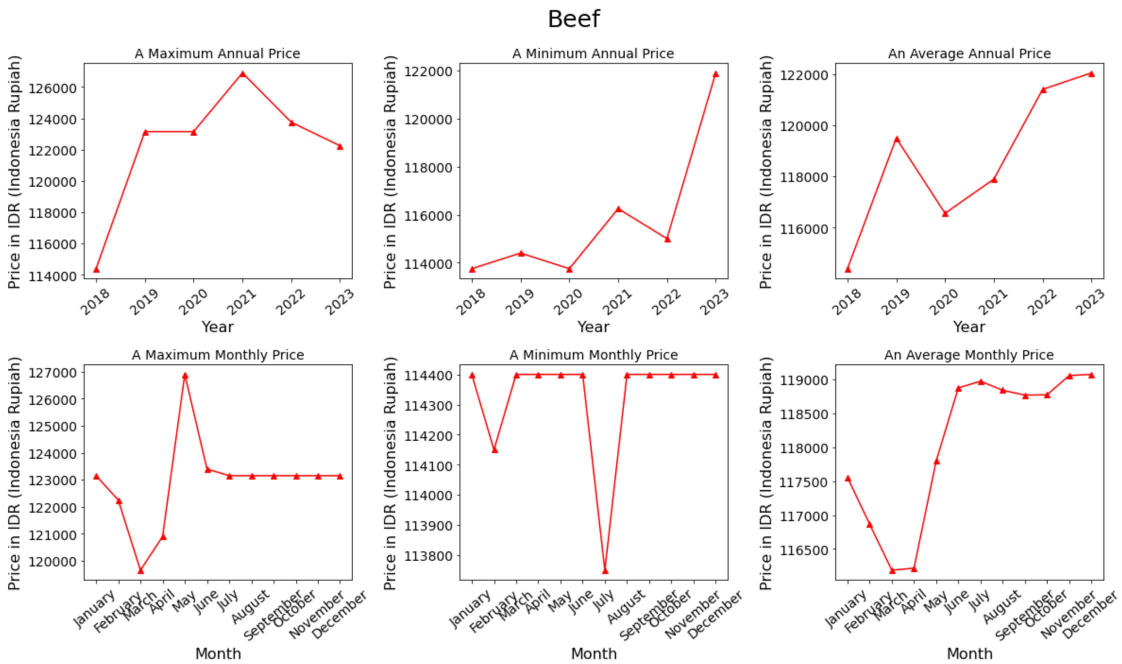

Figure 6 The price of beef

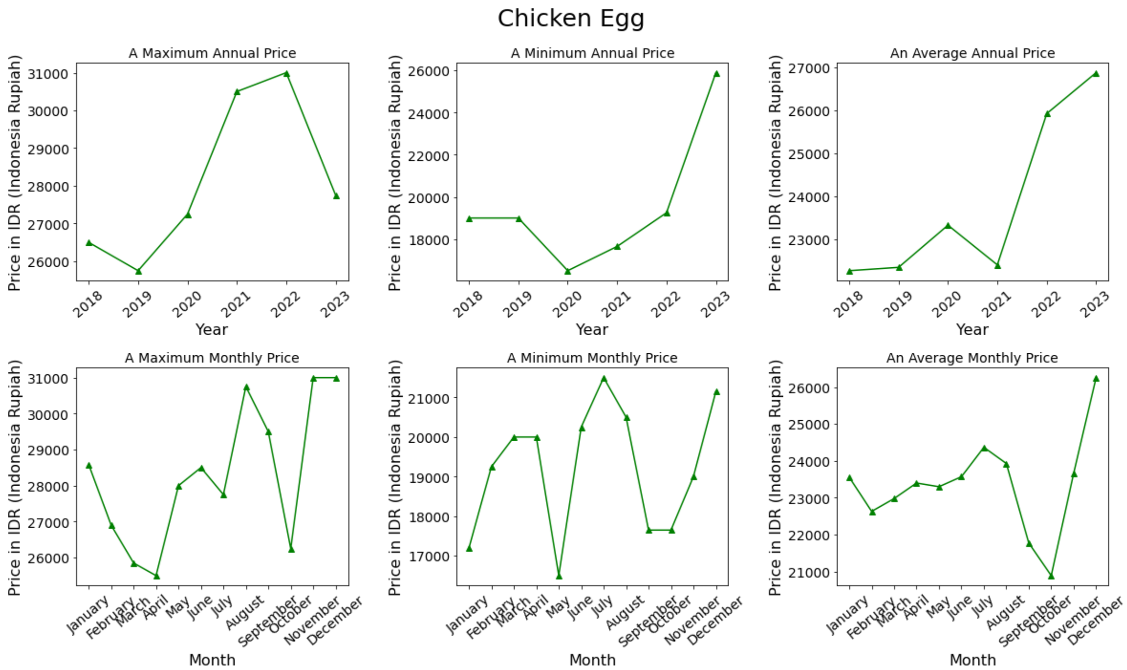

Figure 7 The price of chicken egg

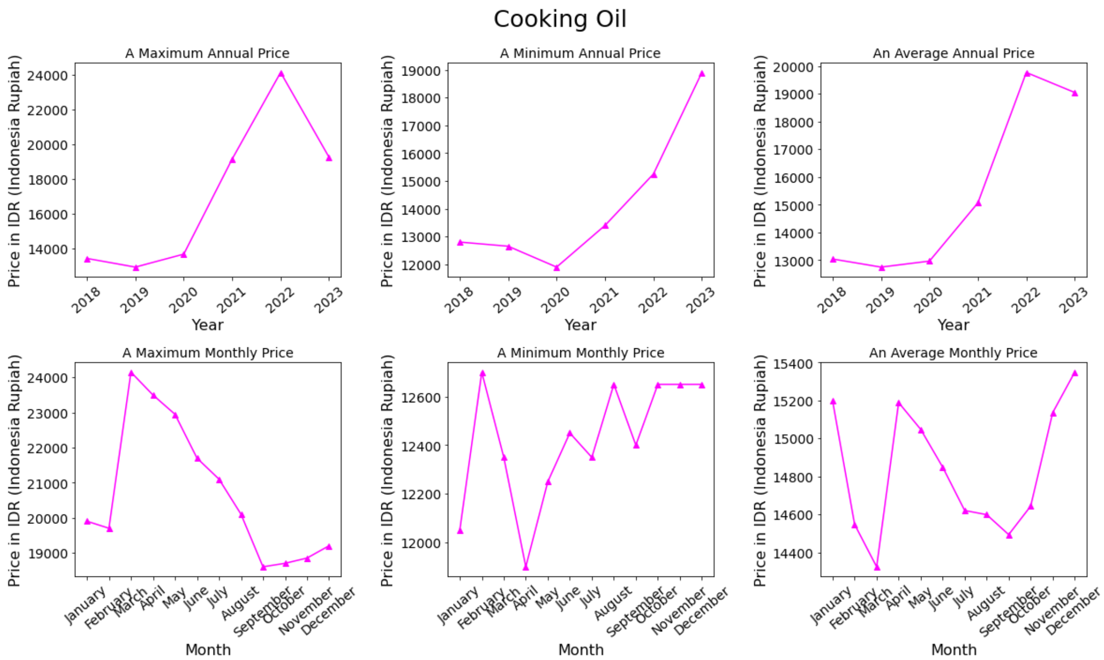

Figure 8 The price of cooking oil

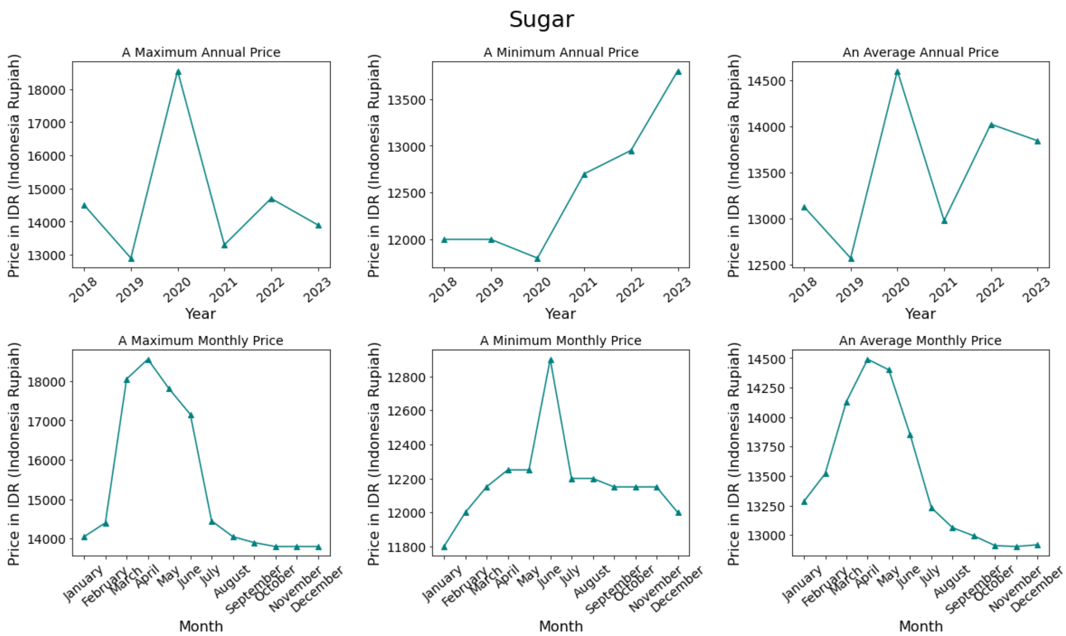

Figure 9 The price of sugar

Table 2 The Pearson correlation coefficient

	Rice	Beef	Chicken Egg	Cooking Oil	Sugar
Rice	1	-0.253255	-0.132917	-0.231921	-0.015311
Beef	-0.253255	1	0.308934	0.526371	0.072032
Chicken Egg	-0.132917	0.308934	1	0.490992	0.184243
Cooking Oil	-0.231921	0.526371	0.490992	1	0.173771
Sugar	-0.015311	0.072032	0.184243	0.173771	1

The Pearson correlation coefficient matrix is displayed in Table 2. Beef has a positive correlation with chicken egg and cooking oil. It indicates that their price increase and decrease simultaneously. Rice has negative correlations to beef, chicken egg, and cooking oil. It implies that when the rice price increases, the prices of beef, chicken egg, and cooking oil decreases and vice versa. Chicken egg and beef have a positive correlation, so their prices move together. The correlation coefficients reveal that beef, chicken egg, and cooking oil have a positive correlation each other.

CONCLUSION

In conclusion, LSTM is successful to use models for forecasting the price of rice, beef, chicken egg, cooking oil, and sugar. This research develops 5 LSTM models where a model fits to predict each foodstuffs price. The LSTM models produce MAPE scores as 0.12%, 0.03%, 0.72%, 0.36%, and 0.08% for forecasting rice, beef, chicken egg, cooking oil, and sugar, respectively. The trend analysis found that the price of beef, chicken egg, and cooking oil have an increasing trend in annual average. Future research is analyzing the causality of fuel prices, meteorological conditions, and foodstuffs prices.

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