Indonesia's Food Commodity Price Forecasting using Recurrent Neural Networks

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***Abstract*— Managing strategic commodities prices in the market is considered an important task since they have a significant contribution to the calculation of the inflation rate. Inflation management has a strong connection to the public's economic activities and buying power. To aid this problem, it is necessary to find the best forecasting model that can predict commodities daily price. This paper aims to find the best prediction model between Recurrent Neural Network (RNN) variants, LSTM and GRU, in forecasting the daily price of three Indonesia's strategies commodities: rice, broiler meat, and chicken egg. The result shows that the GRU model achieves higher accuracy in predicting the daily price of rice, broiler meat, and chicken egg, based on two evaluation metrics Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The GRU model also managed to finish the computational process faster than LSTM by ~20 seconds.**

***Keywords*— Forecasting, strategic commodity, LSTM, GRU**

I. INTRODUCTION

Food commodity price fluctuation often contributes to a country's inflation rate since food is people's most basic need. Various factors affecting the price of food commodities are supply stock, demand, flow and cost of distribution, and the success rate in producing food crops [1].

Inflation management is closely connected to people's buying power and poverty. Controlling inflation of essential goods is crucial since it contributes to the most considerable portion of most households' expenditure. Statistics Indonesia [2] stated that the subgroup food from food, drinks, and tobacco group has gone through an inflation of 2,05% (month-to-month) in April 2022. Compared to last year, April 2021, the number of Price Consumer Index (IHK) for subgroup food experienced inflation of 5,33% (year-to-year). For this reason, appropriate policies and efforts to stabilize prices and availability of essential goods are being carried out intensively by the Ministry of Trade, along with regional governors and other relevant Ministries/Agencies.

According to UU No. 7/2014 about Trading and Presidential Regulation No. 71/2015 regarding establishment and retention of basic needs and essential goods, the Ministry of Trade (Kemendag) is given the task and authority to maintain price stability and availability of essential goods within the market, as the means to control inflation by managing food commodities inflation in particular.

The National Strategic Food Price Information Center determines the 10 strategic food commodities consisting of rice, shallots, garlic, chili pepper, cayenne pepper, beef, chicken meat, chicken eggs, sugar, and cooking oil. Strategic commodities is defined as commodities that contribute greatly to the calculation of inflation rate. The Central Statistics Agency (BPS) assigned a value to each commodity based on total household expenditure during 2012 Survey of Living Cost. The value is used to calculate the national inflation rate of Consumer Price Index (IHK). Each commodity's value can be seen in Table 1.

TABLE I. WEIGHTED VALUE OF EACH STRATEGIC COMMODITY

Commodity	Weight	Commodity	Weight
Rice	3,81	Sugar	0,53
Broiler meat	1,2	Red Chili	0,37
Chicken eggs	0,67	Shallot	0,29
Beef	0,59	Garlic	0,17
Cooking oil	0,57	Cayenne Pepper	0,13

The formulation of related policies requires a robust and accurate database to ensure effectivity once implemented. Obtaining comprehensive and continuous data regarding future prices and supply of essential goods on a national scale calls for appropriate forecasting techniques. The forecasting result will be used to formulate early warnings regarding goods with fluctuating prices, map policy target areas, and measure the scope of policy needed.

II. RELATED WORKS

Accurate food price forecasting is crucial to assist the government in maintaining a stable inflation rate. A popular technique often used in time series forecasting is Autoregressive Integrated Moving Average (ARIMA). Muhardi et al. [3] used ARIMA to predict the production and price of rice and maize in Central Sulawesi. However, ARIMA has several weaknesses. Namely, the model does not consider the latent dynamics in the data, can only be applied to one variable (univariate), and there is an assumption of linearity of the time series data [1][3].

Nugroho et al. [5] used Vector Error Correction Model (VECM), which is a multivariate model of the Error Correction Model (ECM) to predict the spot price of coffee. ECM can explain the relationship of the observed variables in the past and the present [5]. Mardianto et al. [1] compared two estimators, namely Fourier series and kernel, using nonparametric regression for cases with multi-response in predicting the prices of ten strategic commodities in Indonesia. Xiong et al. [6] proposed a hybrid model that combines the decomposition procedure using seasonal-trend based on loess (STL) with extreme machine learning (ELM) called STL-ELM to predict the prices of cabbage, chili, cucumber, long beans, and tomatoes.

Anggraeni et al. [7] used Artificial Neural Network (ANN) to forecast the price of chili, which fell short compared to Holt-Winter's forecast result. Later, the method was improved by combining ANN with ARIMAX to produce a better result, this time in forecasting the price of rice [8]. Mahto et al. [9]

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compared ANN with ARIMA to forecast sunflower and soybean prices. This research showed that ANN model could provide more accurate results in predicting commodity prices than the ARIMA model.

Recurrent Neural Network (RNN) is a neural network that can process sequential data. RNN produces the output by taking into account the information in the previous time step and the new input. Although RNN is excellent at handling sequential data, it can not handle long-term dependencies due to vanishing gradients problems caused by multiplicative computations during the training process [10].

In 1977, Hochreiter and J. Schmidhuber [11] developed a variant of RNN called Long short-term memory (LSTM) to tackle the vanishing gradient problem. Later in 1994, Cho et al. [11] introduced Gated Recurrent Unit (GRU) is a part of the modified RNN model from LSTM. GRU has a more straightforward structure and has faster computational capabilities than LSTM [12]. The basic structure of the GRU consists of an update gate and a reset gate.

Sadefo Kamdem et al. [4] used LSTM to forecast the prices of several commodities, including West Texas Intermediate (WTI) crude oil, Brent oil, silver. Ly et al. [13] compared the result of LSTM and ARIMA in predicting prices of cotton and oil, which resulted in ARIMA having a better performance than LSTM. Sabu and Kumar [14] also compared the performance of LSTM and ARIMA in predicting arecanut's price. The result showed that LSTM had the best forecasting result. Busari and Lim [15] tried to improve the performance of LSTM and GRU in forecasting time series data by adding Adaptive Boosting algorithm [16]. The result showed that AdaBoost-LSTM and AdaBoost-GRU perform better than classic LSTM and GRU, with AdaBoost-GRU having the best result out of all four models.

This paper aims to compare and find the best forecasting method between RNN variants, LSTM and GRU, to forecast the daily price of rice, broiler meat, and chicken egg, as the top three commodities with the biggest average weekly per capita expenditure according to Statistics Indonesia [17]. Average expenditure per capita is the result of calculating the amount of expenditure used by households for consumption purposes for one month divided by the number of members of each household [17]. Especially for the consumption of food commodities, expenditures are calculated for the past one week so that the figures that appear are the average figures per week.

III. Material and Methods

This study is done in several stages, including data preparation, model formulation, and model evaluation.

A. Data Preparation

In this research we use daily prices of Indonesia's strategic commodities from January 2016 to December 2021. The commodities chosen are rice, broiler meat, and chicken egg. The data was obtained from Market and Basic Needs Monitoring System (SP2KP) website provided by Ministry of Trade. Statistical description of the data is shown in Table II. Missing data is treated by filling them with the exact value from the previous time step.

The data is divided into training and testing datasets, with 80% for training and 20% for testing. A min-max normalization is used to transform the data into a range between 0 and 1 to avoid noise and speed up the computing process [13], [18].

TABLE II. Statistical Description of the Data

Commodity	Mean	Standard deviation	Min	Max
Rice	10582.99	187.72	8500	11751
Broiler meat	33194.04	2281.15	217000	450000
Chicken egg	24694.48	1535.02	119000	320000

B. Model Formulations

Long short-term memory (LSTM) is a type of Recurrent Neural Network (RNN) introduced by Hochreiter and Schmidhuber [19] to solve the vanishing gradients problems in traditional RNN. The memory cells in LSTM allow for any critical information to be retained and irrelevant information to be discarded. There are three gates in a memory cell: an input gate, an output gate, and a forget gate.

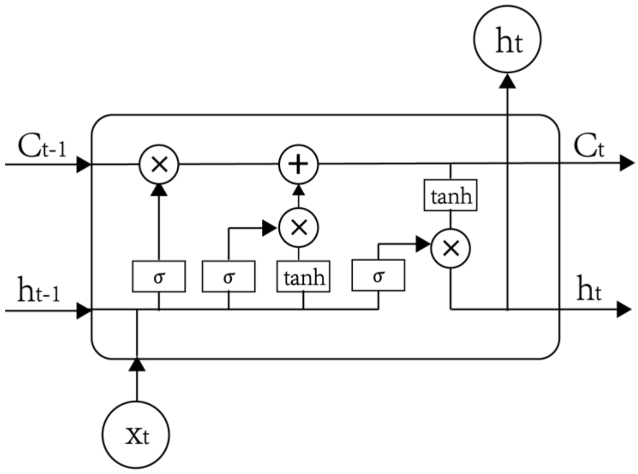


Fig. 1. LSTM network architecture [20]

The output of each gate is calculated by the equations below:

$$f_t = \sigma_g\left(W_f x_t + U_f h_{t-1} + b_f\right) \quad (1)$$

$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \quad (2)$$

$$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \quad (3)$$

$$\hat{C}_t = tanh(W_c x_t + U_c h_{t-1} + b_c) \quad (4)$$

$$C_t = f_t \odot c_{t-1} + i_t \odot \hat{C}_t \quad (5)$$

$$h_t = o_t \odot tanh(c_t) \quad (6)$$

The output of forget gate, input gate, and output gate are shown as f_t, i_t, and o_t, respectively. Each gate has different weight matrices and bias vector values. The mechanism starts with x_t as the new input of time step t to the memory cell. The input is then multiplied by weight matrices W and added by b as the bias vector, and the output of the previous cell h_{t-1}, which is multiplied by weight matrices U. The vector then goes through a sigmoid activation function σ. Input cell state $\hat{C}_t$ is calculated as a hyperbolic tangent (tanh) function to decide the amount of information added from the new input [4]. The value of cell state C_t is obtained by calculating the output of forget gate and input gate. Lastly, the final output of the cell h_t is calculated as the hadamard product of output gate o_t and the hyperbolic tangent result of C_t.

Gated Recurrent Unit (GRU) is a simplified version of LSTM network proposed by Cho et al. in 2014 [10]. Unlike LSTM, GRU only has two gates in its memory cell: reset gate (r_t) and update gate (z_t). The roles of reset gate and update gate are pretty much similar to LSTM three-gates mechanism, reset gate decides how much information to be discarded while update gate decides how much information to be kept [15].

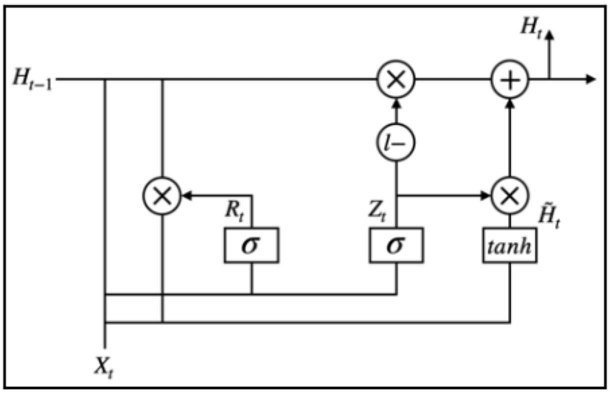


Fig. 2. GRU network architecture [21]

$$z_t = \sigma_g(W_z x_t + U_z h_{t-1} + b_z) \tag{7}$$

$$r_t = \sigma_g(W_r x_t + U_r h_{t-1} + b_r) \tag{8}$$

$$\hat{h}_t = tanh(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h) \tag{9}$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \hat{h}_t \tag{10}$$

The update gate and reset gate output are shown as z_t and r_t, respectively. Both gates use new information at time t, x_t, and information from the previous cell state h_{t-1}, multiplied by weight matrices W and U and added by bias vector b. σ is a sigmoid function used in reset gate and update gate. Candidate vector $\hat{h}_t$ is calculated using a hyperbolic tangent function. The operational symbol $\odot$ marks the element-wise multiplication. At last, the output of the cell h_t is calculated by combining the output from update gate z_t, previous cell sate h_{t-1}, and candidate vector $\hat{h}_t$.

A few hyperparameters are tested before the dataset is fed into the model. Table III shows the number of the hyperparameters tested and the bold ones mark the chosen value. The number of hidden layers is set to be two with 200 neurons each. The input is the previous 5 days of commodity's daily price. The epoch is set to be 100 and the batch size is 64.

TABLE III. MAE AND MAPE VALUE FOR LSTM AND GRU RESULT

Hyperparameters	**Value**
Layer	1, **2**, 3
Neuron	100, **200**
Epoch	**100**, 200

C. *Model Evaluation*

Model evaluation is done by utilizing Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - x_i| \tag{11}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - x_i}{x_i}\right| \tag{12}$$

Where y_i is the predicted value, x_i is the actual value, and n is the number of data points. MAE measures the average difference between the predicted and actual value; thus, it is easy to interpret and is widely used by statisticians to evaluate the forecasting model's performance [15]. MAPE shows the relative average of the error. A value closer to zero marks the better forecasting model for both MAE and MAPE.

IV. RESULTS AND DISCUSSION

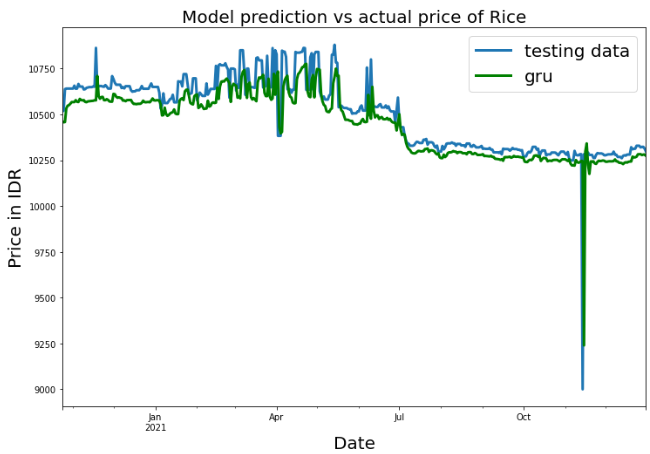
The result of the evaluation of GRU and LSTM models in forecasting rice, broiler meat, and chicken egg daily prices is shown in Table III. GRU shows a slightly better performance than LSTM in predicting rice, broiler meat, and chicken egg daily price based on the MAE and MAPE scores. Both models show minimal values for the MAPE that are almost close to zero, which means that the LSTM and GRU models did an excellent job predicting the daily price.

TABLE IV. MAE AND MAPE VALUE FOR LSTM AND GRU RESULT

Commodity	**Model**	**MAE**	**MAPE (%)**
Rice	LSTM	56.338	0.536
	GRU	53.434	0.509
Broiler meat	LSTM	369.210	1.064
	GRU	347.176	0.999
Chicken egg	LSTM	359.802	1.436
	GRU	302.800	1.205

A. *Rice daily price prediction*

Fig. 3 compares the actual price and the price predicted by LSTM and GRU from the testing data. The picture shows that LSTM and GRU did a great job predicting daily rice prices. Predictions from LSTM and GRU were able to converge with the line of the actual price when the price is stable, with GRU being slightly closer. During the sudden decrease towards the end, when the daily price of rice reached Rp9,000/kg, both LSTM and GRU managed to predict the prices close to the actual price, which are Rp9,484.836/kg and Rp9,251.377 respectively.



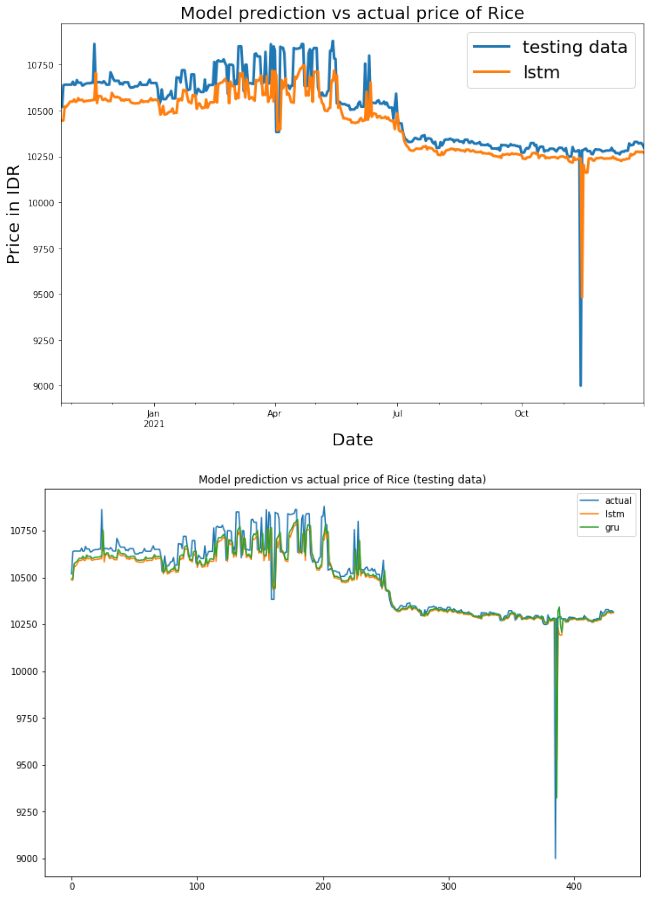


Fig. 3. Plot of actual and predicted price of rice

Table III shows that the MAE score for LSTM and GRU are 56.338 and 53.434. MAE shows the average difference between the predicted and the actual value. In this case, both models showed a deficient number compared to the mean of the whole data of rice daily price, which is 10582.99 (Table II). The MAPE scores of the predicted price are also considerably low, which are 0.536% for LSTM and 0.509% for GRU. From both measurements, it can be said that GRU predicted the daily price of rice better than LSTM.

B. Broiler meat daily price prediction

Fig. 4 presents the graph of the actual daily price of broiler meat to the predicted price by LSTM and GRU. From the picture, it can be seen that both LSTM and GRU were able to handle a few outliers quite well by predicting a value close to the actual price.

From Table II it is shown that the mean daily price of broiler meat is 33194.04. Table III shows that the MAE score for LSTM is 369.210, and GRU is 347.176. Both values are very short compared to the mean daily price of broiler meat. The MAPE values for the forecasted price by LSTM and GRU are 1.064% and 0.999%. Based on the MAE and the MAPE score, it can be determined that GRU gave a better forecasting result compared to LSTM.

C. Chicken egg daily price prediction

Fig. 5 shows the actual chicken egg daily price plot compared to the forecasted price using LSTM and GRU. From the figure, it can be seen that both LSTM and GRU did a great job at forecasting some sudden decreases in chicken egg daily price. Although there seems to be a gap between the actual and the predicted prices, both GRU and LSTM models were able to mimic the daily trend of the actual prices.

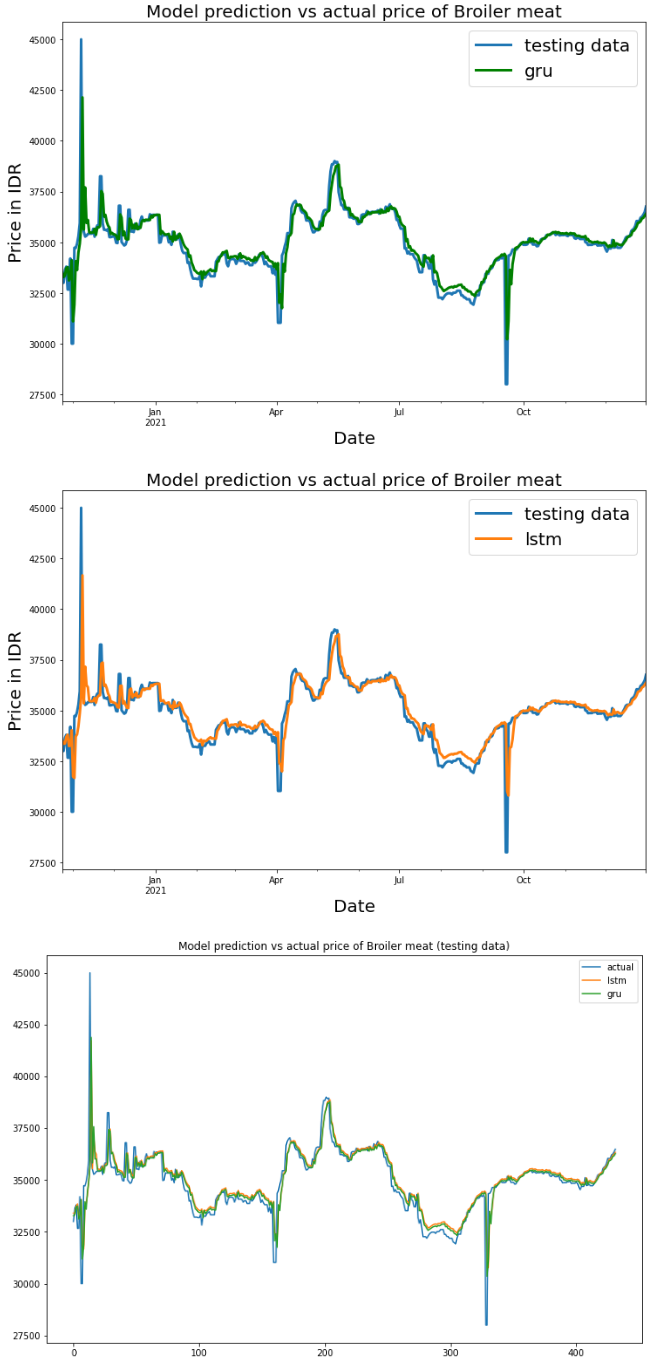


Fig. 4. Plot of actual and predicted price of broiler meat

Table III shows the value of MAE of the predicted price using LSTM and GRU: 359.802 and 302.8. The differences are considered low compared to the mean value of the daily chicken egg price, which is 24694.48. The MAPE score for the forecasted price using LSTM is 1.436%, while the GRU forecasted price earned 1.205%. Based on the evaluation metrics, it can be decided that GRU did a better job at forecasting the daily price of chicken egg.

D. Model execution runtime measurement

The LSTM and GRU prediction models were built using Keras on Google Colaboratory notebooks, where both models had the same hyperparameters. This experiment measured the total time it takes to execute each model until the prediction result is out. Table IV shows the total execution runtime from each model in predicting the daily price of rice, broiler meat, and chicken egg. The GRU model managed to finish the computation faster than LSTM by ~20 seconds for all three commodities. This was possible because GRU integrates the cell and hidden states in its network architecture [15]. In the future, data size will become even more massive, and it may be needed to incorporate different kinds of variables. Therefore, a prediction model with a faster computation process like GRU would have advantages compared to LSTM.

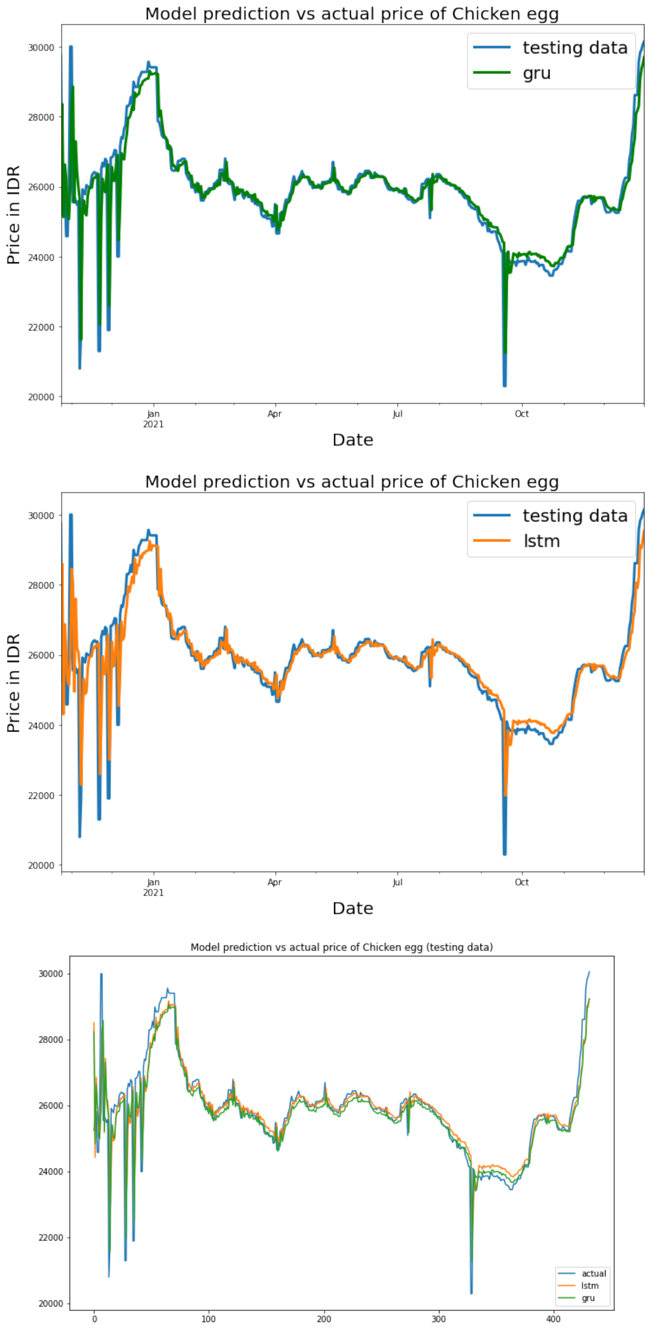


Fig. 5. Plot of actual and predicted price of chicken egg

TABLE V. TOTAL EXECUTION RUNTIME OF LSTM AND GRU MODELS

Commodity	LSTM (seconds)	GRU (seconds)
Rice	209	174
Broiler meat	215	189
Chicken egg	183	162

Knowledge regarding the future price of strategic food commodities can reduce uncertainty and helps the government, as the main stakeholder, formulate food price policies (import and export) and map specific target areas for different policies to keep the prices stable [22]. The models evaluated in this research can be used to predict the future prices of food commodities with high accuracy. Farmers and traders can also utilize information about future price data to construct a few strategies to minimize loss [23].

V. CONCLUSION

In this study, LSTM and GRU models were applied to forecast the daily price of three of Indonesia's strategic commodities: rice, broiler meat, and chicken egg. The best prediction model was selected by measuring the two evaluation metrics, MAE and MAPE. The prediction result of LSTM and GRU models achieved MAE scores as follows: 56.338 and 53.434 for daily rice price, 369.210 and 347.176 for broiler meat daily price, and 359.802 and 302.8 for chicken egg daily price, respectively. The MAPE scores for the prediction result obtained by LSTM and GRU are as follows: 0.536% and 0.509% for daily rice price, 1.064% and 0.999% for broiler meat daily price, and 1.436% and 1.205% for chicken egg daily price, respectively. The MAE and MAPE scores showed that GRU predicted all three commodities' daily prices slightly better than LSTM. However, there was not much difference between the MAE and MAPE scores of LSTM and GRU, which means that LSTM also did an excellent job at forecasting the daily price of rice, broiler meat, and chicken egg. During the execution of the forecasting models, GRU finished the computation process around 20 seconds faster than LSTM, which again shows its superiority over LSTM.

The next step of this research is to also include other factors affecting food price such as supply number, international price, as well as special events during the year to be used as predictors to determine food price. More thorough selection in deciding neural network models' hyperparameters is also needed to achieve an even higher accuracy.

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