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Study of Gated Recurrent Unit (GRU) and Extreme Gradient Boosting (XGBoost) Methods in Predicting the Closing Price of Garudafood Putra Putri Jaya Tbk., Indonesia

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***Abstract*—*Time series analysis has become an important method in understanding and predicting the behavior of stock prices in financial markets. Gated Recurrent Unit (GRU) and Extreme Gradient Boosting (XGBoost) are methods that can be used to perform stock price predictions. The aim of this research is to compare the GRU and XGBoost methods in predicting the closing share price of Garudafood Putra Putri Jaya Tbk., Indonesia. The research results from comparing these two methods show that the GRU method is better than XGBoost. This is based on the MAPE and RMSE GRU values, namely 1% and 6.42 respectively. Meanwhile, the XGBoost method obtained a MAPE value of 1.8% and RMSE of 8.78. From these results it can be concluded that the use of the GRU method is better than XGBoost in predicting the closing price of PT Garudafood Putra Putri Jaya Tbk., Indonesia because it produces smaller MAPE and RMSE values.*

Keywords*—*Time Series Analysis, Stocks, GRUS, XGBoost, MAPE, RMSE.

I. Introduction

Time series analysis can be used to estimate future values in historical data, both from univariate and multivariate data. Some methods for predicting univariate time series data include Gated Recurrent Unit (GRU) and Extreme Gradient Boosting (XGBoost). GRU method has a simple architecture but can provide prediction accuracy comparable to other RNN models. Meanwhile, XGBoost is one of the methods with ensemble learning that can handle a large number of datasets.

GRU is an improved derivative of the RNN model. GRU has a simpler design that speeds up data processing [1]. Despite its simplicity, GRU provides a level of prediction accuracy comparable to other RNN models. Meanwhile, XGBoost is a machine learning technique that can be used for regression or classification, especially effective for structured data such as time series. XGBoost has significant advantages in overcoming overfitting, by using advanced regularization techniques and an iterative approach in its learning. In addition, XGBoost is able to manage large datasets efficiently [2].

Based on this explanation, this research will compare the GRU and XGBoost methods to predict the closing stock price of Garudafood Putra Putri Jaya Tbk., Indonesia The comparison is carried out with the aim of determining the most accurate model with the smallest error value measured using Mean Absolute Percent-age Error (MAPE) and Root Mean Square Error (RMSE). thus, it can be known which method is better in predicting the closing stock price of Garudafood Putra Putri Jaya Tbk., Indonesia.

II. Literature Review

Deep learning techniques, such as the Gated Recurrent Unit (GRU) method and machine learning Extreme Gradient Boosting (XGBoost) models, are very effective for time series analysis and have been widely used for prediction. Several deep learning and machine learning models can be used as data prediction methods. for example, the GRU and XGBoost methods.

A. Gated Recurrent Unit (GRU)

Gated Recurrent Unit (GRU) is a type of RNN designed to overcome the missing gradient in RNN. The GRU method is designed to solve the vanishing gradient problem that often appears in standard recurrent neural networks [3,4]. This method is also considered a variation of the LSTM method. However, GRU has fewer parameters than LSTM because it does not have output gates. In univariate time series forecasting, GRU can perform better than LSTM [5]. Inside the GRU, there are 2 components that regulate the flow of information called gates, namely the update gate and the reset gate. The reset gate formula is as follows:

$$r = \sigma(W_{xr} \,. X_t + W_{hr} \,. h_{(t-1)} + b_r) \tag{1}$$

And for the calculation of the gate update using the following formula:

$$z = \sigma(W_{xz} \,. X_t + W_{hz} \,. h_{(t-1)} + b_z) \tag{2}$$

Next is to determine the hidden state candidate using the tanh activation function with the calculation of the formula as follows:

$$\tilde{h} = tanh(W_{xh} \,. X_t + r \ast W_{hh} \,. h_{(t-1)} + b_z) \tag{3}$$

The next step is to produce the final output as a hidden state using the following formula:

$$h = z \ast h_{(t-1)} + (1 - z) \ast \tilde{h} \tag{4}$$

with, r = reset gate, z = update gate, $\tilde{h}$ = candidate *hidden state*, h = output, σ = sigmoid activation function, W_{xr} , W_{hr} = parameter weight for reset gate, W_{xz}, W_{hz}= parameter weight for update gate, W_{xh}, W_{hh} = parameter *weight for candidate*

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hidden state, X_t = input data, $h_{(t-1)}$= hidden state from the previous time step, b_r, b_z = bias value.

A. Extreme Gradient Boosting (XGBoost)

Extreme Gradient Boosting (XGBoost) is one of the en-semble learning that combines several dicision tree models and gradually develops the model by adding a new tree that corrects the error of the previous tree [6,7,8]. The final model of the boosting technique is a combi-nation of a set of several models with n iterations so as to produce the smallest error value of the residuals.

In the XGBoost algorithm, each tree will provide updated weights, which are then summed up when making predictions and fed into the decision function [9]. The function can be written as follows:

$$\hat{y}_i^{(t)} = \sum_{k=1}^{t} f_k(x_i) \quad (5)$$

with: $\hat{y}_i^{(t)}$ = final tree model, $f_k(x_i)$ = new model built, t = total number of models from base tree models.

III. Methodology

The data used in this research is daily closing stock price data from June 2, 2020 to April 29, 2024 (n=947) of Garudafood Putra Putri Jaya Tbk., Indonesia obtained from https://finance.yahoo.com.

The first step taken in this research was to carry out descriptive statistical analysis and data visualization. Next, data preprocessing was carried out to check for missing values in the data and divided the data into two, namely 90% training data and 10% test data. After the data is divided into training data and test data, the data is analyzed using the GRU and XGBoost methods. To measure the best model, it can be seen from the MAPE and RSME values. The smallest MAPE and RSME values are the best model.

IV. Result and Discussion

Descriptive statistical analysis of the closing stock price data of Garudafood Putra Putri Jaya Tbk., Indonesia is presented in Table 1 below.

TABLE 1. Descriptive Statistic

Variable	Mean	Median	Std.Dev	Maximum	Minimum
Close	420.55	434	99.34	590	244

Table 1 above shows that the closing stock price has a minimum value of 244 and a maximum of 590 with an average of 420.55 and a median value of 434. Standard deviation of 99.34 indicates that the distribution of the closing share price is relatively large around the average. This means that the closing share price is often quite far from the average, indicating that there are significant fluctuations in the value of this stock over time. To get clear understanding of the data distribution, the scatter plot of the data is given in Fig. 1.

Based on Fig. 1, it can be seen that the graph shows the movement of closing stock price data of from 2 June 2020 to 29 April 2024 tends to be fluctuated.

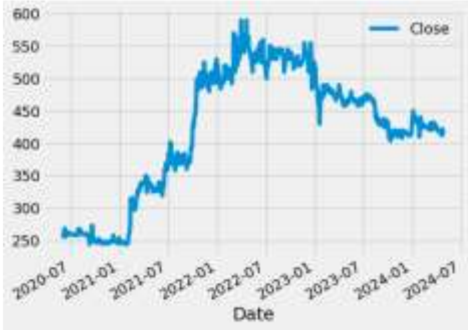

Fig. 1. Plot of stock closing prices.

Furthermore, before further data processing is carried out, the data was first divided by comparing training data and test data. A ratio of 90:10 from a total of 947 data, namely 90% (n=852) was used as training data, while 10% (n=95) of the data was used as test data. This ratio of 90:10 is the best ratio for data prediction using GRU and XGBoost methods compared to 80:20 or 70:30. After the ratio data was determined, the data was normalized. Data normalization needs to be done because the sigmoid function used has a value range between 0 and 1. Closing stock price data will be normalized using the min-max scaling method so that the value is in the range 0 to 1 using the following formula.

$$x' = \frac{x - min}{max - min} \quad (6)$$

with, x' = normalization result; x is the i-th data, min= minimum value of the data, max= maximum value of the data.

The following step was to perform hyper-parameter tuning. This tuning process involves a series of experiments to ensure the selected parameters are optimal when incorporated into the GRU model. The following are the parameters that will be used in the GRU method.

TABLE 2. Hyperparameter Tuning of GRU prediction Data

Hyperparameter	Value
Epoch	100
Loss function	Mean Squared Error
Learning rate	0.001
Activation	Tanh, Sigmoid
Hidden neuron	16, 32, 64
Batch size	16, 32, 64

From the results of the process above, the best parameters were obtained as given in Table 3.

TABLE 3. Hyperparameter search result with GridSearch GRU

Hyperparameter	Value
Activation	2 hidden layer: Tanh Output layer: Sigmoid
Hidden neuron	GRU unit: 64 Dense unit: 64
Batch size	16
Learning rate	0.001
Epoch	100

Finally, the GRU model was applied to the test data to make predictions. This prediction is important as an evaluation of model performance to ensure optimal results. Following are the prediction results of the GRU model.

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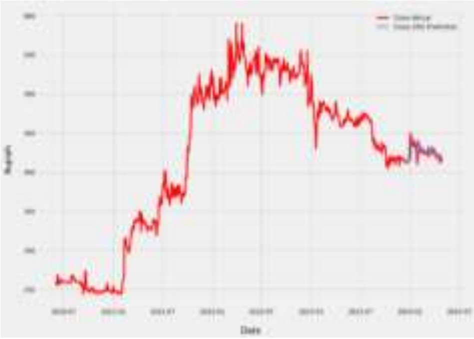

Fig. 2. Plot of GRU model prediction results

Based on Fig. 2, it can be seen that the GR model obtained produces graphs that show fluctuations similar to the patterns found in the actual data distribution. This shows that the model has succeeded in capturing the complexity and variation of the data.

Hereafter, data analysis was carry out using the XGBoost method. This method includes graphical decomposition that helps understand the intrinsic structure of data such as trend, seasonality, and residuals. The following is a decomposition graph of closing price data for shares of Garudafood Putra Putri Jaya Tbk., Indonesia.

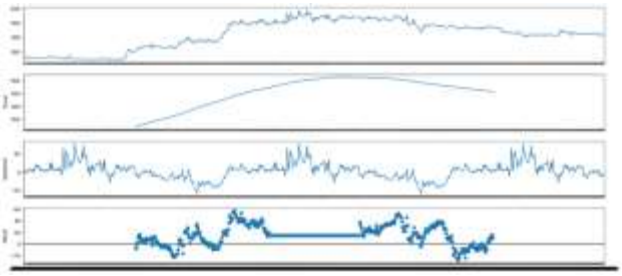

Fig. 3. XGBoost model decomposition

From Fig. 3, it can be seen that the closing price of the stock initially rises and then tends to fall, with a clear seasonal pattern. The residual graph shows small random fluctuations around the zero value. Therefore, this stock price data is suitable for use in training a stock price prediction model.

Furthermore, the process of Model refinement using hyperparameter tuning method in GridSearch. Hyperparameter tuning is used in the XGBoost method as follows:

TABLE 4. Hyperparameter Tuning of XGBoost Prediction Data

Hyperparameter	Value
N_estimators	500, 600
Learning_rate	0.1
Max_depth	8, 10, 12, 15
Gamma	0.005, 0.001, 0.05, 0.01
Random_state	42
Min_child_weight	1, 2, 3, 4
Subsample	0.8, 1
Colsample_bytree	1
Colsample_bylevel	1

The resulting best parameters are as follows:

TABLE 5. Hyperparameter Tuning of XGBoost Prediction Data

Hyperparameter	Value
N_estimators	600
Learning_rate	0.1
Max_depth	10
Gamma	0.01
Random_state	42
Min_child_weight	3
Subsample	0.8
Colsample_bytree	1
Colsample_bylevel	1

Furthermore, predictions were made using the XGBoost model to test the data. This prediction was performed as a model evaluation to obtain optimal performance. Fig 4. display the result of XGBoost model prediction.

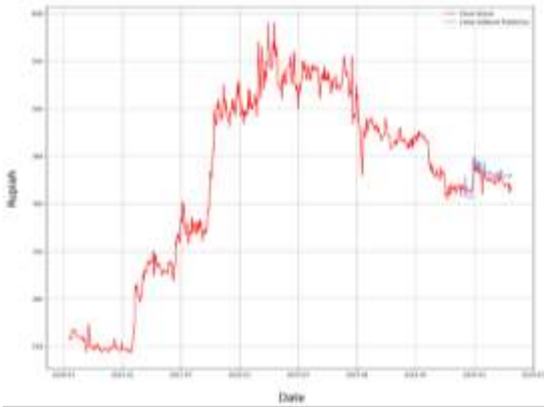

Fig. 4. XGBoost model prediction result Plot

From Fig. 4, it can be seen that the model can reproduce fluctuations similar to the patterns present in the actual data. This shows that the model can capture the complexity and variability of the dataset well.

After obtaining predictions from both GRU and XGBoost models, an evaluation of their performance was conducted to determine the most optimal model. The best models that can be used for prediction are those that show lower error values. To determine the best model, the best model can be created, the model selection criteria can use MAPE and RMSE. Table 6 gives the results of MAPE and RMSE values from GRU and XGBoost models.

TABLE 6. Comparison results of GRU and XGBoost models

Models	MAPE	RMSE
GRU	1%	6.42
XGBoost	1.8%	8.78

As it is seen in Table 6 the MAPE and RMSE values in the GRU model are smaller than the XGBoost model, namely the GRU model obtained MAPE values of 1% and RMSE values of 6.42, while in the XGBoost model obtained MAPE and RMSE values are smaller at 1.8% and 8.78. This means that the GRU model has a smaller error than the XGBoost model, so the GRU model can be said to be better at predicting the closing price of Garuda food shares compared to the XGBoost model.

V. Conclusion

Based on the results of the above research, it can be concluded that:

1. In the GRU method, the results obtained MAPE value of 1% and RMSE value of 6.42.
2. While the XGBoost method obtained the results of the MAPE value of 1.8% and RMSE 8.78.
3. Based on the results of MAPE and RMSE calculations on the GRU and XGBoost methods with 90% splitting data as training data and 10% as testing data shows that the GRU method is superior in predicting the closing price of PT Garuda food Putra Putri Jaya Tbk. because it obtains smaller MAPE and RMSE values.

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