

Comparison of LSTM, XGBoost, and GRU Methods in Forecasting the Effect of Boycott Actions on PT. Unilever Indonesia Tbk's Stock Prices

1st Suhaila Prima Putri
Bachelor Programme of Statistics Department, Faculty of mathematics and natural sciences Universitas Padjadjaran Sumedang, Indonesia
suhailaprimaputri@gmail.com

2nd Carissa Egytia Widiantoro
Bachelor Programme of Statistics Department, Faculty of mathematics and natural sciences Universitas Padjadjaran Sumedang, Indonesia
carissawidiantoro12@gmail.com

3rd Silvi
Bachelor Programme of Statistics Department, Faculty of mathematics and natural sciences Universitas Padjadjaran Sumedang, Indonesia
2018silfi@gmail.com

4th Muhammad Kamil Dipinto
Bachelor Programme of Statistics Department, Faculty of mathematics and natural sciences Universitas Padjadjaran Sumedang, Indonesia
dipintom3@gmail.com

Abstract—Over the past year, global attention has focused on the genocide against Hamas in Palestine by Israel, with many companies, including Unilever, indirectly supporting Israel financially. Unilever, a UK-based multinational and the third-largest company in the world has faced significant boycotts due to its perceived support of Israeli action. PT Unilever Indonesia Tbk is part of Unilever and has high-value stock listed in LQ45 on the Indonesia Stock Exchange (IDX), with a Return on Assets (ROA) of 47.4%. This research compares LSTM, GRU, and XGBoost models for stock of PT Unilever Indonesia Tbk. The result shows that the GRU model has the lowest MAPE at 0.0221, the LSTM model follows with a MAPE of 0.092472, and XGBoost Model has the highest MAPE at 0.26454. GRU model indicates superior accuracy than LSTM or XGBoost. This comparison aims to identify the most suitable method for forecasting PT Unilever Indonesia Tbk stock prices.

Keywords—Boycott, GRU, LSTM, Unilever XGBoost

I. INTRODUCTION

The word "boycott" comes from an English agricultural agent named Captain Charles Boycott who utilised a high-rate rental collection strategy in Ireland in 1880. The Irish community is furious and unhappy about this approach. A boycott is a type of movement that raises public awareness of rights and issues that particular parties are fighting for. It falls under the category of *jihad fi sabilillah* in relation to property. This is due to the fact that the duty to carry out a boycott is founded on the concept of jihad, creating a new kind of the jihad [1]. Genocide, as defined by the KBBI, is the deliberate killing of a race or nation in large numbers. This boycott movement is well-liked by social media users and has rapidly expanded throughout the globe, especially to Indonesia. Boycotting is a way for someone or a certain group to become alienated from something. A few examples of actions that demonstrate the

implementation of a boycott are blockading, embargoing, and blacklisting. Conversely, boycott categories cover the various facets of the boycott, such as its methods, components of action, and kinds of products that are boycotted. A boycott's aspects include the people who started it, whether they are local authorities, international organisations, or the community. There are two ways to address a boycott in the interim: the direct approach, which involves the boycotted party directly[2].

In the last year the world has been shocked by the genocide against Hamas in Palestine by Israel. Many companies in the world indirectly provide for Israel through their finances. Examples of companies involved in supporting the genocide carried out by Israel are Unilever, Starbucks, McDonald's, etc. Therefore, Indonesian people are carrying out a massive boycott of products that support the Israeli genocide as a form of supporting Palestine. The impact of the boycott had an impact on the movement of brand shares. It is anticipated that this boycott campaign will be able to exert financial pressure on Israel in response to its brutal policies towards Palestine [3]. The boycott of Unilever products is the one that is discussed in this study. The global corporation Unilever has its main office in London, England. Unilever manufactures body care products, beverages, food, and cleaning. Based on revenue in 2012, Unilever ranked third globally among household products manufacturers, after P&G and Nestlé. Additionally, Unilever is the world's biggest manufacturer of food spreads, including margarine.

This dedication and collaboration led to a global boycott of Unilever products, particularly in Indonesia. On the one hand, this is a smart policy in order to create a deterrent effect for anyone who supports Israel. The reason for this boycott reports that a portion of the country's revenue was being utilised, either directly or indirectly, to support Israel. directly in the form of monetary support that is utilised to advance the development of armaments and infrastructure in order to fortify Israel's presence in Palestinian territory. Israel's policy towards Palestine is an indirect form of assistance. Thus, abstaining is a moral way to support the Palestinian people's struggle and to express

disapproval for Israel's invasion of PalestineClick or tap here to enter text..

One thing that can be seen from the boycott is through the movement of shares. The share price is the price set by a company for another party who wants to take over the shares[4]. PT Unilever Indonesia Tbk shares are among the expensive stocks included in LQ45, consisting of 45 stocks with the highest liquidity and largest market capacity in BEI. The Return On Assets (ROA) for PT Unilever Indonesia was 47.4%, including lofty values. A high ROA suggests that the company can make a high level of profit as well[5]. Getting paid for your work is the primary goal of investing committed. These benefits may take the form of capital gains—the difference between the market price and the nominal price—or dividends, which are the company's profit-sharing payments[5]. It is crucial for investors to forecast share prices before determining how much capital they should invest. As markers of earnings, the boycott campaign against Unilever products has a lot of advantages and prospects, but it also has a number of drawbacks and risks[6].

Unilever's share position will decline from 22 June 2017 to 22 June 2024. Condition of PT. Unilever shares can be seen in Figure 1 below:



Source: Finance Yahoo

Fig. 1. PT. Unilever's share price movements 22 June 2017 to 22 June 2024

Based on Syahrul's research, the LSTM model is used to forecast stock prices UNVR has an RMSE value of 115.32 and a MAPE of 1.5%, so UNVR's share price will experience a decline on 3 January 2022 to February 14 2022 [7]. LSTM approach yields a MAPE of 2.11% based on Dian Islamiyat Putri's research, allowing us to anticipate Unilever shares using the LSTM method[8]. Based on the results of research conducted by Clara Tanudy, et.al regarding gold price prediction in Indonesia using the GRU method, it was concluded that the GRU method was successfully used to forecast gold prices, the best data training results with training data parameters of 70%, timestep 20, epoch 100, and batch size 16 has the best performance with an R-Squared value of 0.97, MAE of 300.17 and RMSE of 17.33[9]. It was determined that the XGBoost model's optimization on PT share prices was based on research done by Tiyas Astutiningsih, et al. Models made by United Tractors Tbk. are precise. The hyperparameters that were utilized gamma: 0.01, learning rate: 0.05, max depth: 15, and n estimator: 200 lead to the best model. Based on experimental findings, the model's MAPE value was found to be 3.89%. The model is said to be accurate based on MAPE[10]. Based on the findings and Andrew Nilsen's discussion, it is possible to conclude that the Gated Recurrent Unit (GRU) model has the highest level of accuracy when comparing the historical closing

prices of shares listed on the LQ45 index with three different models: Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), and Long Short-Term Memory (LSTM)[11]. Based on Xiwen Jin and Chaoran Yi's research on stock close time predictions using the ordinary least squares method (OLS), Lightgbm, XGBoost, random forest, LSTM and GRU models. Obtained MSE results LSTM 7.06, GRU 6.26, Random Forest Regressor 12.02, XGB Regressor 7.55, Linear Regression 6.64 and LGBTM Regressor 6.94, obtained by GRU model is the most accurate (lowest MSE)[12].

Estimates for Unilever shares were not provided by prior research when comparing the LSTM, GRU, and XGBoost models. Therefore, in order to compare the LSTM, GRU, and XGBoost models, researchers will examine Unilever Indonesia shares that were boycotted by Unilever associates who supported the atrocities carried out by Israel. To find out stock predictions per day, you need the right method. Researchers want to research forecasting methods that are suitable for Unilever Indonesia stock data using comparison three methods, LSTM, GRU, and XGBoost. By comparing these three methods, it is hoped that it can help find the right forecasting method for Unilever shares in the future.

II. STUDY AREAS

A. PT Unilever Indonesia Tbk

Unilever is a multinational company based in the UK. This company is the third largest in the world in the global household products industry, with various brands under it [13].

PT Unilever Indonesia Tbk has been operating since 1933 and became publicly listed in 1982 and its shares are recorded and traded on the Indonesia Stock Exchange. Unilever Indonesia proudly sponsors 40 brands that are divided into 2 segments, namely Home, Beauty & Wellbeing and Personal Care ("B&W and PC") and Nutrition & Icecream ("N&I"). These products include soap, shampoo, cleaning products, toothpaste, fragrances, cosmetic products, instant spices, sauces, tea, and even ice cream.

The trademarks under Unilever Indonesia, include Lux, Citra, Sunsilk, Lifebuoy, Dove, Clear, Sahaja, Pepsodent, Close Up, Sunlight, Super Pell, Vixal, Wipol, Rinsol, Molto, Rexona, Vaseline, Pond's, and so on.

Unilever is one of the companies that was boycotted. The reason why Unilever was targeted was when one of their companies called Ben & Jerry's decided to stop selling ice cream in West Bank, Palestine, during the Israeli occupation in 2021. Unfortunately, Ben & Jerry's intentions to respect Palestine were countered by Unilever bosses [14].

B. Data Utilized

In this study, we use secondary data obtained from yahoo.finance. The dataset used has a time range from 22 June 2017 until 21 June 2024, totaling 1735 days. The data used for prediction is Unilever Indonesia stock data using the close price dataset.

III. METHODOLOGY

A. Data Preprocessing

The data has been normalized to make the real number fall between 0 and 1. The following equation is used in the min-max normalization approach [15]:

$$x_{norm,i} = \frac{x_i - x_{min}}{x_{max} - x_{min}}, i = 1, 2, \dots, t \quad (1)$$

When the minimal data is x_{min} , the highest data value is x_{max} , and the normalisation value is x_{norm} . Subsequently, the dataset is split into two subsets: data used for training and data for the purpose of testing. For LSTM and GRU ratio of 80% for training data, 10% for testing data, and 10% for validation data is used to divide the data. And for XGBoost ratio of 80% for training data and 30% for testing data.

B. Training, Testing, and Validation Each Model

Proceed to the training data stage by employing the LSTM, GRU, and XGboost algorithms after finishing the data pretreatment step. Each model is trained using training data as part of the training process. The testing procedure is used utilizing testing data, which is subsequently evaluated based on the outcomes of the training model, in order to ascertain the model's efficacy. Validation data is used in the meantime by the validation process.

Parameters are required during the process of training and testing data to create the LSTM, GRU, and XGBoost models to obtain the best model. Trial-and-error testing is utilized to determine the ideal parameters for model development. The parameters to be employed in this investigation are suggested in Tables 1, 2, and 3.

TABLE I. PARAMETER DESCRIPTION LSTM

PARAMETER	VALUE
Learning rate	0.0005
Epoch	100
Optimizer	Adam
Loss	Huber

TABLE II. PARAMETER DESCRIPTION GRU

PARAMETER	VALUE
Batch size	32
Epoch	200
Optimizer	Adam
Verbos	1

TABLE III. PARAMETER DESCRIPTION XGBOOST

PARAMETER	VALUE
N estimation	1000

C. Denormalized

The denormalization process returns the output results that are still in the shape of the range 0-1 corresponds to the actual value of the data. Calculation of the denormalization process refers to [8] using the following equation:

$$d = y(max - min) + min \quad (2)$$

Where d is the denormalization value, y is the prediction result, max is the value of maximum data, and min is the minimum value of the data

D. Model Evaluation

The Mean value Absolute Percentage Error (MAPE) was used in this study to evaluate the model's performance. The percentage of errors/errors obtained based on the actual value with the projected result value is called the Mean Absolute Percentage Error, or MAPE. [15] making use of the subsequent formula:

$$MAPE = \frac{1}{n} \sum_{i=1}^n \frac{|y_i - \hat{y}_i|}{y_i} \times 100\% \quad (3)$$

where y_i is the actual value of the data, \hat{y}_i is the value of the predicted result, and n is a lot of data. The scale for assessing prediction accuracy based on MAPE values was developed [8] in Table 4.

TABLE IV. CRITERIA FOR MAPE VALUE

MAPE SCALE	INTERPRETATION
<10%	Highly accurate
10-20%	Accurate
20-50%	Quite accurate
>50%	inaccurate

E. Long Short Term Memory (LSTM) Method

The LSTM method is one of the most common used RNNs for processing and forecasting time series, is designed to avoid long-term dependence issues [14]. In addition, long-term retention of information is made possible by LSTM's additional mechanism for handling the vanishing gradient problem. RNNs are frequently used to process and forecast time data. It is intended to stop problems with long-term reliance. In short, the LSTM architecture consists of several memory blocks that are connected subnetworks repeatedly. The memory blocks in the network are responsible for both controlling the information flow between the cells and preserving the network's state over time.

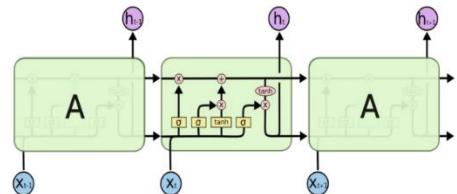


Fig. 2. LSTM architecture block diagram

Three gates make up the LSTM architecture: the forget gate (f_t), the input gate (i_t), and the output gate (O_t). To delete data from the cell state, use the forget gate (f_t). The purpose of the input gate (i_t) is to determine what new information enters the cell state, and the output gate (O_t) is to filter out relevant information from the cell state's flow and show it as output. The LSTM process's equation relates to [8], with b in the equation.

$$f_t = \sigma(W_{fh}[h_{t-1}], W_{fx}[X_t], b_f) \quad (4)$$

$$i_t = \sigma(W_{ih}[h_{t-1}], W_{ix}[X_t], b_i) \quad (5)$$

$$\tilde{C}_t f_t \quad (6)$$

$$= \tanh(W_{ch}[h_{t-1}]W_{fh}[h_{t-1}], W_{cx}[X_t]W_{fx}[X_t], b_c) \quad (7)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (7)$$

$$= f_t(W_{fh}(h_{t-1}), W_{fx}(X_t), b_f) \quad (7)$$

$$O_t = \sigma(W_{oh}[h_{t-1}], W_{ox}[X_t], b_o) \quad (8)$$

$$h_t = O_t * \tanh(C_t) \quad (9)$$

where x_t is the input value, W is the weight, b is the bias, h_{t-1} is the output of time $t - 1$, C_{t-1} is the memory cell state of the previous cell, and h_t is the final output.

F. Gated Recurrent Unit (GRU) Method

GRU (Gated recurrent unit) is one type of RNN. This model introduces a gating structure to read long-distance information. GRU is similar to LSTM, except that it has fewer parameters since it lacks an output gate[16]. GRU only introduces two gates namely update gate (z_t) and reset gate (r_t)[17]. The architecture of the GRU can be seen in the figure below.

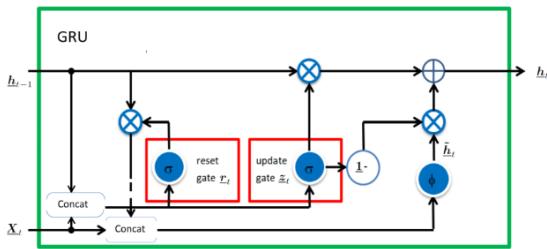


Fig. 3. GRU architecture block diagram

The update gate is useful for channeling information from inputs and previous outputs to the next cell, while the reset gate is useful for determining which past information should be forgotten[17]. The operation of GRU can be seen through the following formulae.

$$z_t = \sigma(W_z * [h_{t-1}, x_t]) \quad (10)$$

$$r_t = \sigma(W_r * [h_{t-1}, x_t]) \quad (11)$$

After resetting gate and updating gate, the candidate value status of GRU is \tilde{h}_t and the final output is h_t with the following formula:

$$\tilde{h}_t = \tanh(w_{\bar{h}} * [r_t * h_{t-1}, x_t]) \quad (12)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \bar{h}_t. \quad (13)$$

G. Extreme Gradient Boosting (XGBoost) Method

XGBoost was developed by Chen and Guestrin in 2016, is an algorithm that incorporates the boosting model proposed by Friedman. XGBoost is an ensemble model that efficiently implements decision trees to create a combined model. This combined model has better predictive performance than the individual techniques used on their own [18]. XGBoost can be utilized as a feature-selection method to identify important features for prediction from high-dimensional time-series data, discarding any redundant features in the process [17].

The main idea of XGBoost is to iteratively add weak trees with varying weights to the model. Each new tree aims to closely approximate the residuals of the previous predictions [18], which is represented as follows,

$$\hat{y}_t = \sum_{k=1}^K f_k(x_i) \quad f_k \in F \quad (14)$$

For the objective function of XGBooxt can be expressed as Equation (15)

$$Obj^{(t)} = \sum_{i=1}^n I(y_i, \hat{y}_i^{(t)}) + \sum_{i=i}^t \Omega(f_t) + constant \quad (15)$$

If Taylor expansion is used to approximate the objective function, the original objective function can be written as Equation (16)

$$Obj^{(t)} = \sum_{j=1}^T \left[\sum_{i \in I_j} g_i w_j + \frac{1}{2} \left(\sum_{i \in I_j} h_i + \lambda \right) \right] \gamma T \quad (16)$$

$$g_i = \partial_{\hat{y}^{(t-1)}} l(y_i, \hat{y}_i^{(t)}), \quad h_i = \partial_{\hat{y}^{(t-1)}}^2 l(y_i, \hat{y}_i^{(t-1)}) \quad (17)$$

IV. RESULT

A. LSTM

In this method, several steps were taken to build an LSTM model for data prediction. First, the data was imported and prepared using libraries such as numpy, pandas, matplotlib, seaborn, and tensorflow. The data was then read and preprocessed, including normalization to ensure consistent data scaling. Several regulation techniques are implemented to prevent overfitting of the model.

The data is divided into training, testing, and validation data with 80% of the data used for training and 10% for testing and 10% for validation. The following plot is obtained



Fig. 4. Application of the training, testing, and validation data for LSTM model

After the data splitting process, the LSTM model was trained using the normalized training data. The model was trained using the Adam optimizer and mean squared error (MSE) as the loss function.

Model evaluation was conducted by comparing actual data with predicted data. In the training evaluation stage, the prediction results showed good agreement with the actual data, indicated by low error values. In the validation stage, the model was tested with previously unseen data to measure the model's generalization ability. The validation results showed that the model was able to predict quite well, although there were slight deviations between the actual data and the predicted data. The comparison plots between actual data and predicted data in both the training and validation stages indicated that the LSTM model performed quite well in capturing patterns and trends in the data.



Fig. 5. Actual training data and predict training data for LSTM model

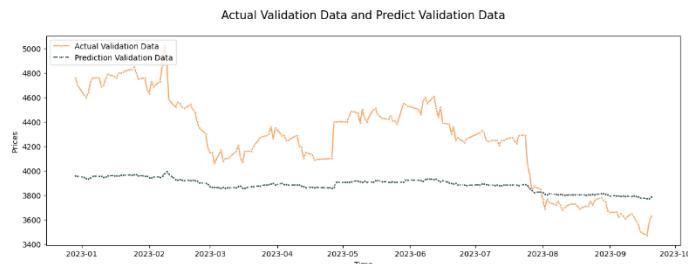


Fig. 6. Actual validation data and predict validation data for LSTM model

The trained LSTM model was used to predict the stock prices of Unilever for the period from June 14, 2024, to June 28, 2024. The forecasting results were presented in the form of tables and plots to visualize the predictions generated by the model.

TABLE V. TABLE STOCK PREDICTION RESULTS 15 DAYS AHEAD WITH THE LSTM MODEL

Date	Forecast
2024-06-22	3008.685303
2024-06-23	2971.650635
2024-06-24	2979.929932
2024-06-25	2951.467773
2024-06-26	2952.908691
2024-06-27	2930.125732
2024-06-28	2927.077148
2024-06-29	2908.062744
2024-06-30	2902.076904
2024-07-01	2885.569336
2024-07-02	2877.667969
2024-07-03	2862.837158
2024-07-04	2853.696045
2024-07-05	2839.992188
2024-07-06	2830.054443



Fig. 7. Graphic prediction results 15 days ahead with the LSTM model

To evaluate the accuracy of the forecasting, a comparison plot between actual data and forecast data was made. This plot included training, validation, and forecast periods. In this plot, the actual data from the training and validation periods was compared with the predictions from the LSTM model. The plot indicated that the model's forecast results followed the patterns and trends of the actual data quite well. Although there were some deviations between the actual data and the forecast results, overall, the model was able to capture the main dynamics of stock price movements.



Fig. 8. Comparison of actual data and forecast data

A plot is then created that combines the actual data and the forecasting data to provide a clear visualization of the model's performance and prediction accuracy.

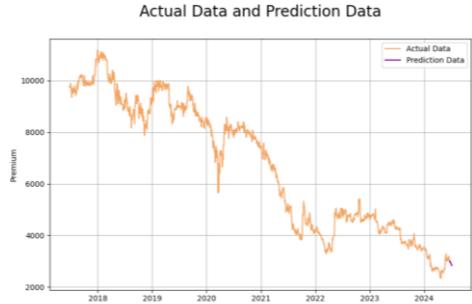


Fig. 9. Visualization of actual data and forecast data

Based on the analysis and forecasting results, it can be seen that the LSTM model used has sufficient ability to forecast Unilever's stock price in the short term. The model successfully follows the pattern and trend of historical stock data, although there are some small deviations in the forecasting results.

B. GRU

The first thing to do at GRU is to clean the data. As explained earlier, the stock data used is only in the close price dataset. Therefore, it is necessary to remove variables other than close price. Then the data is divided into 80% train data, 10% validation data, and 10% testing data. The following plot shows the splitting data.



Fig. 10. Training, testing, and validation data on GRU model

Then, the data is normalized for analysis needs. After that, the GRU model is built by adding layers, dropouts, and dense. the optimizer used is adam and loss function mean square error. Then, the model is trained with an epoch of 200 and a batch size of 32.

Comparing the original value of the data with the predicted value obtained to evaluate the model that has been formed. From figure 10 it can be seen that there is not too much difference between the original training value and the predicted training value. Similar results are also obtained for the original validation value and the validation prediction value as shown in figure 11. This shows that the prediction model provides a low error.

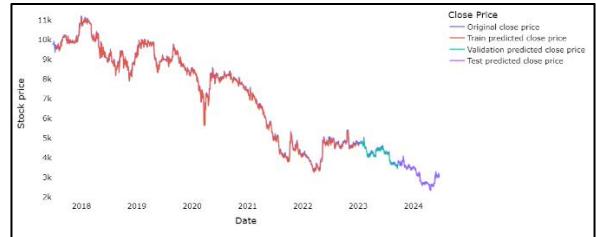


Fig. 11. Comparison between original value and predicted value on GRU model

The stock price of Unilever Indonesia is then predicted for the period from June 22, 2024 to July 6, 2024 using the GRU model created. The prediction results are then visualized using tables and graphs. The results of the GRU model indicate that the stock price of Unilever Indonesia is likely to decline further over the next 15 days.

TABLE VI. TABLE STOCK PREDICTIONS FOR 15 DAYS AHEAD WITH GRU MODEL

Date	Forecast
2024-06-22	3008.685303
2024-06-23	2971.650635
2024-06-24	2979.929932
2024-06-25	2951.467773
2024-06-26	2952.908691
2024-06-27	2930.125732
2024-06-28	2927.077148
2024-06-29	2908.062744
2024-06-30	2902.076904
2024-07-01	2885.569336
2024-07-02	2877.667969
2024-07-03	2862.837158
2024-07-04	2853.696045
2024-07-05	2839.992188
2024-07-06	2830.054443

Unilever Stock Prices 22 June 2024 - 6 July 2024

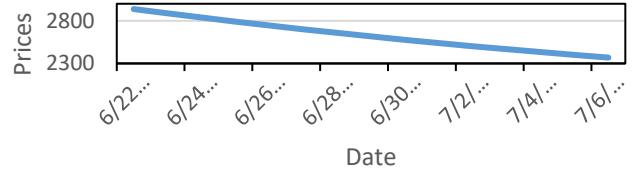


Fig. 12. Stock prediction plot for 15 days ahead with GRU model

A plot is then created that combines the actual and predicted data to help visualize the model and the accuracy of the prediction. As can be seen from the prediction results, the GRU model is able to predict stock data in the short term. The GRU model is able to read patterns and trends from the data.

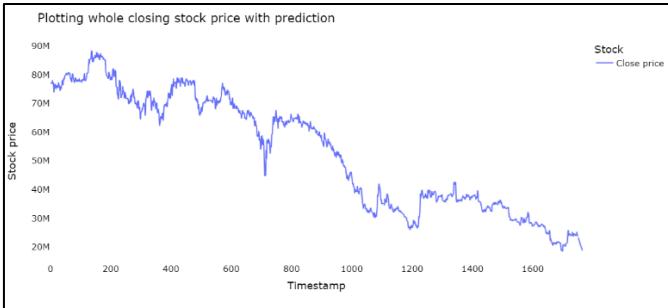


Fig. 13. Plot of actual data and predicted data on GRU model

C. XGBoost

First stage of building XGBoost model is read the file, drop the unused variables, and change the date to the same date format as pandas used in Python. Time series feature is made based on the datetime index, so we made the date as index. After that, make visualization of the distribution of training and testing data. The distribution is done with a percentage of 80:20. Data training will be used to create models and testing data for testing the model.



Fig. 14. Application of the training testing data for XGBoost model

The time series feature made are date, day of week, quarter, month, year, day of year, and day of month. Figure [14] is the graphic visualization of the distribution of training and testing data. The purpose of making the feature is to forecast using XGBoost model. Figure [15] is plot of feature importance for modeling XGBoost.

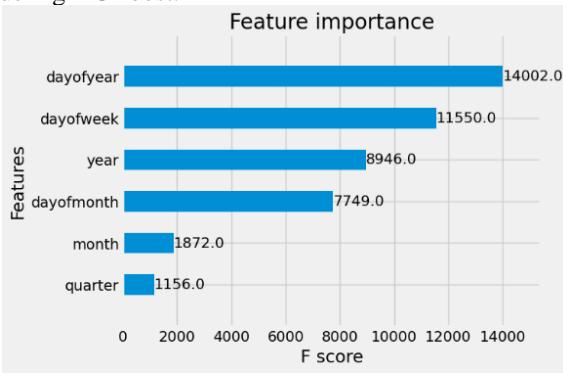


Fig. 15. Plot feature importance

The following are the results of fitting and predicting testing data which is shown in figure [16]. In figure it can be seen that the prediction it seems to follow the data pattern but there is a significant gap between actual and predicted testing data. We obtain MAPE value of 26.54 % based on testing data, which is

quite accurate according to criteria for MAPE value. The red line shown the prediction result and the blue line shows the original data.



Fig. 16. Plot actual vs predicted data

After creating a XGBoost model based on the results of training and testing data. The trained XGBoost model was used to predict the stock prices of Unilever for the period from Juni 22, 2024 to July 6, 2024. The forecasting result were presented in the form of table and plot to visualize the predictions generated by model.

TABLE VII. STOCK PREDICTIONS RESULTS 15 DAYS AHEAD WITH THE XGBOOST MODEL

Date	Forecast
2024-06-22	3008.685303
2024-06-23	2971.650635
2024-06-24	2979.929932
2024-06-25	2951.467773
2024-06-26	2952.908691
2024-06-27	2930.125732
2024-06-28	2927.077148
2024-06-29	2908.062744
2024-06-30	2902.076904
2024-07-01	2885.569336
2024-07-02	2877.667969
2024-07-03	2862.837158
2024-07-04	2853.696045
2024-07-05	2839.992188
2024-07-06	2830.054443

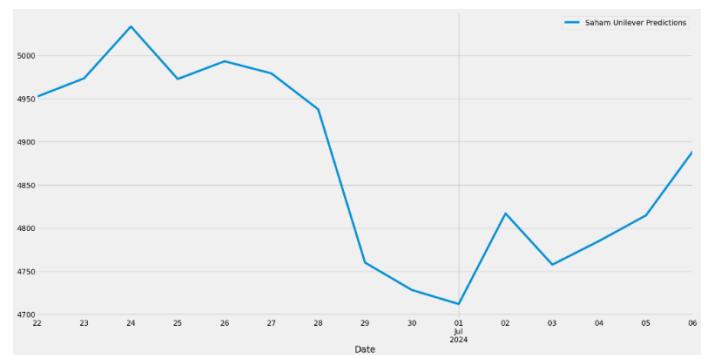


Fig. 17. Graphic prediction results 15 days ahead with the XGBoost model

From figure [17], shows the movement of Unilever's stock prices from June 22, 2024, to July 6, 2024. The stock price is forecasted to decline significantly from around 4950 to below 4750 by July 1. It then shows a recovery, rising to

approximately 4900 by July 6, with some fluctuations in between. This illustrates the predicted volatility and overall trend of the stock within the specified period.

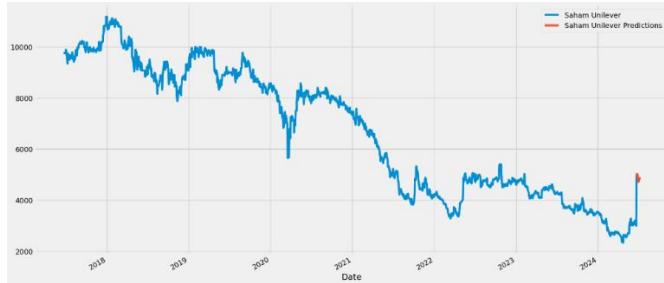


Fig. 18. Visualization of actual data and forecast data

Figure [18], show plot to display both the actual data and the forecasted data, offering a clear visualization of the model's performance and prediction accuracy. The red line show the prediction result and the blue line shows the original data.

D. Comparison the Model

TABLE VIII. PERFORMANCE COMPARISON

Methods	MSE	MAE	RMSE	MAPE
LSTM	508541.703	634.29	713.1211	0.092472
XGBoost	975059.159	907.20	975059.15	0.26454
GRU	8025.534	69.41	89.5853	0.0221

A comparison of the models (LSTM, XGBoost, and GRU) can be seen for each PT Unilever Tbk stock. The GRU model has a lowest MAPE than the other model. This indicates that the GRU model can provide more accurate predictions in modeling the data of PT Unilever Tbk Stock. The other hand, LSTM also have the second lowest MAPE, this also indicates that the LSTM model also capable of providing accurate predictions in modeling the data of PT Unilever Tbk.

The XGBoost model has the highest MAPE, which, according to the MAPE criteria, indicates that the model is accurate. However, compared to the LSTM and GRU models, XGBoost is slightly less accurate.

V. CONCLUSION

This paper compares stock price prediction using three different models: LSTM, GRU, and XGBoost. Based on the analysis, LSTM and GRU show the best results, while XGBoost has the worst results. Nonetheless, all models can predict the trend of the closing stock price quite well and can predict the closing stock price of PT Unilever Indonesia Tbk without major errors.

The results of the analysis show a significant decline of the stock price of PT Unilever Indonesia Tbk. One factor that may have contributed to this decline was the boycott of the company's products in favor of Israel. The boycott affected consumer and investor confidence, which then negatively impacted the company's share price. This is also relevant to the

Sustainable Development Goals (SDGs), particularly goal 12 on responsible consumption and production and goal 16 on peace, justice and strong institutions. Companies involved in controversial issues may face challenges that affect their stock performance.

However, predicting stock prices with these models still has shortcomings. The stock market is very complex and is affected by many factors such as policy changes, large buying/selling power, capital volume, and different company information, all of which can affect the accuracy of the model.

Overall, the use of models to predict stock prices has practical uses and can help investors and investment institutions in short-term stock trading. However, further research is needed to systematically verify the feasibility of these models and improve accuracy with the support of statistical techniques. The results of this study provide guidelines for stock price prediction using linear and machine learning approaches.

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Suhaila is a second-year student in the Statistics Department at Padjadjaran University. During her studies, she has actively contributed as a teaching assistant for Database and Nonparametric Statistics courses. This experience has provided her with a deep understanding of statistical theory and its applications in various contexts. She possesses skills in data analysis, statistical programming, and big data processing using tools such as R, Python, SPSS, and others. In addition to her academic achievements, Suhaila is actively involved in faculty survey projects, demonstrating her ability to effectively manage and analyze large datasets. Her dedication and leadership skills are further evident in her role as head of the academic development department on campus, where she organizes workshops and seminars to enhance the academic skills of her peers. Suhaila has also presented several times at national seminars and been involved in research projects focused on using statistical methods to solve real-world problems. Outside of academics, Suhaila is known for her enthusiasm and commitment to continuous learning. Her skills, dedication, and proactive approach make her a valuable asset to the academic and research community at her university.



Carissa is a second-year student majoring in Statistics at Universitas Padjadjaran. Alongside my studies, she is a teaching assistant for a Non-Parametric Statistics course. Her academic journey is fueled by a strong interest in data science, where she aspires to harness statistical techniques to derive meaningful insights. She has practical experience conducting surveys, which has enhanced my understanding of data collection and analysis. In the implementation of statistical analysis, she has honed her skill in utilizing Python, R, SPSS, and other. She also had the opportunity to present her research findings with her team at a national and international seminar, the research is focused on using statistical methods. In terms of leadership skills, she currently has a role as head of the survey division on campus, she organizes and conducts training sessions about the survey. With effective communication and time management, she was recognized for her ability to collaborate with her team smoothly. Carissa is known for her commitment to continuous learning and enhancing her skills to achieve her goals.



Silvi has been a student majoring in Statistics at Padjadjaran University since 2022. During her second year of undergraduate studies, she became a teaching assistant for the Parametric Statistical Methods course. She is interested in studying statistics, such as data research and data analysis. In addition, she is also interested in operational research related to company management. She has good time management, consistent with her choices, and responsible with her work. In addition to academics, she is active in student organizations and participates in various seminars and workshops to deepen her knowledge. She also has good communication skills and often collaborates with her colleagues in various research projects. She has also been a presenter in a national seminar, where she presented her research results with her team in front of experts and academics from various

institutions. This experience not only enriched her academic horizons, but also improved her skills in conveying information effectively and professionally. Silvi aspires to pursue a career in data science or operational research in a multinational company, hoping to make a significant contribution to data-driven decision making. With her dedication and commitment to statistics, Silvi continues to develop her skills and knowledge to achieve this goal.



Pinto is a second-year student in the statistics program at the Faculty of Mathematics and Natural Sciences, Padjadjaran University. During his two years of study, he has become a course assistant for non-parametric statistical methods. His studies in statistics have enabled him to enhance his knowledge of statistical concepts and his ability to analyze data. He also has a solid grasp of statistical programming, including Python, R, SPSS, and Minitab. Furthermore, Pinto frequently engages in statistical projects, such as survey activities, which demonstrate his enthusiasm for the field of statistics. Pinto has also participated in numerous studies that focus on statistical methods to address real-world issues. He is an active member of the student association, serving as vice chairman, which reflects his ability to manage time, work under pressure, and communicate effectively. Additionally, Pinto often works in groups, which demonstrates his proficiency in collaborating with diverse teams. Pinto is renowned for his dedication and industriousness in attaining his objectives.