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Predicting Price and Risk ICBP Stocks Using GRU and VaR

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Abstrak

Stabilitas dan kemajuan suatu negara sangat erat kaitannya dengan perekonomian, di mana investasi saham memainkan peran penting dalam meningkatkan kesejahteraan masyarakat. Di Indonesia, minat terhadap investasi saham, terutama di sektor pangan yang vital, semakin meningkat karena potensi keuntungan jangka panjang yang menjanjikan. Penelitian ini bertujuan untuk memprediksi harga saham menggunakan model Gated Recurrent Unit (GRU). Hasil prediksi tersebut kemudian akan digunakan dalam perhitungan Value at Risk (VaR) berbasis simulasi historis untuk menganalisis risiko secara lebih komprehensif. Model GRU dipilih karena kemampuannya dalam menangkap pola fluktuasi harga saham yang kompleks dan dinamis, sementara VaR digunakan untuk mengestimasi potensi kerugian maksimum dengan tingkat kepercayaan 95%. Hasil penelitian menunjukkan potensi kerugian maksimum sebesar Rp65.785, yang dihitung melalui integrasi harga prediksi berbasis GRU dengan data historis. Pendekatan ini tidak hanya menghasilkan estimasi risiko yang lebih akurat, tetapi juga memberikan panduan strategis bagi investor dalam memahami potensi keuntungan dan risiko secara lebih menyeluruh. Integrasi prediksi berbasis GRU dan simulasi historis VaR diharapkan dapat menjadi pendekatan baru untuk meningkatkan akurasi perhitungan VaR dengan memanfaatkan data prediksi sehingga menghasilkan analisis risiko yang lebih komprehensif dalam menghadapi dinamika pasar saham.

Kata kunci— *Prediksi harga saham, Analisis risiko, Saham blue chip, Gated Recurrent Unit (GRU), Value at Risk (VaR)*

Abstract

The stability and progress of a nation are closely tied to its economy, where stock investments play a pivotal role in enhancing societal welfare. In Indonesia, interest in stock investments, particularly in the vital food sector, has grown due to its promising long-term profitability. This research aims to predict stock prices using the Gated Recurrent Unit (GRU) model. The predicted results will then be incorporated into the Value at Risk (VaR) calculation based on historical simulation to provide a more comprehensive risk analysis. The GRU model was chosen for its ability to capture complex and dynamic stock price fluctuations, while VaR was utilized to estimate the maximum potential loss with a 95% confidence level. The findings reveal a maximum potential loss of IDR 65,785, calculated by integrating GRU-based predictive prices with historical data. This approach not only provides more accurate risk estimation but also offers strategic guidance for investors to comprehensively assess potential profits and risks. The integration of GRU-based predictions and historical simulation VaR is expected to provide a new approach to improving the accuracy of VaR calculations by utilizing predictive data, thereby offering a more comprehensive risk analysis in addressing the dynamics of the stock market.

Keywords— *Stock price prediction, Risk analytic, Blue chip stock, Gated Recurrent Unit (GRU), Value at Risk (VaR)*

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1. INTRODUCTION

The economy plays a vital role in ensuring a country's stability and progress. Financial systems, especially stock markets, are essential for creating liquidity, mobilizing savings, and providing access to capital, forming the basis for economic growth [1]. Stock investment as a key financial instrument has increasingly gained recognition as a means to optimize income and improve well-being. According to Collin Chiwira, the stock market’s role in stabilizing capital acquisition and supporting economic development makes it a key platform for securing financial stability [1]. Based on the previous statement, people's interest in stock investment grows as they recognize the potential profits it offers.

The food sector plays a vital role in Indonesia's economy, driven by its connection to food security, a critical national and global challenge [2]. This makes the food stock sector highly attractive, reflecting the need to ensure food availability and stability. PT Indofood Sukses Makmur Tbk (ICBP), a leader in Indonesia's food industry, stands out as a strong investment choice due to its market capitalization, liquidity, and frequent trading. The data used in this study consists of historical stock price data for PT Indofood Sukses Makmur Tbk (ICBP), spanning the period from 1 July 2019 to 31 July 2024, sourced from Yahoo Finance. The dataset includes daily closing prices, which are used for stock price prediction and risk analysis. These data points are essential for implementing the GRU model and calculating Value at Risk (VaR) through historical simulation.

Stock investment offers profits but also faces challenges in the form of unpredictable price movements causing significant fluctuations and risks for investors [3]. This uncertainty makes stock price prediction crucial to reducing risks and maximizing profits. The main factors influencing stock movements include news on policies, such as monetary policy, as well as company performance reflected in financial reports. Additionally, national social policy often causes stock movements [4]. The fluctuating and random nature of stock prices makes stock price prediction a complex process and requires advanced analytical techniques.

Predicting stock prices is challenging due to their unpredictable and fluctuating nature. Traditional models like ARIMA have been used to forecast prices based on historical data, but they have limitations. ARIMA works well with simple data patterns but struggles with complex fluctuations [5]. This is where machine learning comes into play as a more advanced approach to analyzing dynamic data. Machine learning algorithms can capture more complex patterns and adapt to rapid market changes, making them an increasingly popular choice for stock price prediction [6].

Several machine learning models commonly used for time series predicted stock prices, are RNN, LSTM, and GRU [7]. The GRU (Gated Recurrent Unit) model, an extension of RNN, was chosen for this study because it offers a simpler structure compared to LSTM while still effectively addressing the gradient vanishing problem commonly found in RNNs. Previous research by Aryati demonstrated how GRU operates using "gates" mechanisms, such as the update gate and reset gate, to control the flow of information within the network [7]. The update gate determines how much information from the previous time step should be retained, while the reset gate decides which information needs to be forgotten.

In addition to stock price prediction, risk management is also an essential component of investment strategies. Value at Risk (VaR) is a statistical measure used to estimate the potential maximum loss in an investment portfolio over a specific period with a certain probability level. In simple terms, VaR provides information on the potential loss that may occur in the worst-case scenario within a given confidence level [8]. Risk prediction here refers to the effort to estimate the level of uncertainty or potential loss in the future, based on the analysis of historical data and assumptions from specific models.

When investors understand the risk level of their assets, they can make more informed allocation decisions [9]. This study calculates Value at Risk (VaR) using historical simulation, which estimates potential losses based on past stock prices without assuming specific statistical distributions. By directly using historical data, it offers a realistic risk projection, helping investors gauge the maximum risk they may face for better decision-making [10]. The combination of stock price prediction using GRU and risk estimation through historical simulation VaR provides a comprehensive view of potential returns and risks, supporting informed investment choices.

Previous research highlights the popularity of Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models for stock price prediction, with GRU often outperforming LSTM. Aryati found GRU achieved a lower MAPE (2.14%) compared to LSTM (2.42%) for UNVR stock [9]. Similarly, Khairunisa demonstrated the effectiveness of GRU for stock prediction, yielding a MAPE of 1.27 for GRU and 1.28 for LSTM, with training epochs set at 50 and 100 [11]. Both studies, however, focused solely on price prediction without addressing loss risk. In risk analysis. In risk analysis, Putri uses Value at Risk (VaR) through historical simulation to identify low-risk portfolios of stocks such as BBRI, BBCA, BNLI, BPTN, and BNBA [8]. Meanwhile, Darman highlighted the benefits of VaR in the banking and mining sectors [10]. However, these studies did not integrate stock prediction with risk analysis.

The research follows a structured methodology consisting of three main stages: (1) data preprocessing, where historical stock price data of PT Indofood Sukses Makmur Tbk (ICBP) is gathered and prepared for analysis; (2) stock price prediction using the GRU model, leveraging its ability to handle complex time-series data effectively; and (3) risk analysis through Value at Risk (VaR), using historical simulation to estimate potential losses based on test data and predicted data from the GRU model, without relying on specific statistical distribution assumptions.

To ensure reliable results, the GRU model's performance is evaluated using Mean Absolute Percentage Error (MAPE) which quantifies prediction accuracy by measuring the deviation between predicted and actual stock prices. After that GRU-predicted stock prices are incorporated into the Value at Risk (VaR) calculation through historical simulation, combining test data with GRU predictions. While the VaR results are not directly evaluated, the study focuses on utilizing GRU predictions to identify future data trends and enhance the historical VaR calculation by expanding the data range for risk estimation.

Existing literature shows no integration of stock price prediction using GRU with loss risk analysis through Value at Risk (VaR), particularly for blue-chip stocks like ICBP. This study fills the gap by using a sequential approach where GRU predicts stock prices from historical data, and the predictions are used to calculate VaR through historical simulation. GRU models complex time series data, while VaR quantifies risk, creating a comprehensive analysis of potential returns and risks. Although applied sequentially, this combination offers a new perspective for investment decisions and has the potential to benefit various economic sectors and investors.

2. METHODS

2.1 Theoretical Framework

2.1.1 Gated Recurrent Unit

Gated Recurrent Unit (GRU) first introduced by Cho in 2014 is a simpler and more efficient variant of Long Short-Term Memory (LSTM) [12]. Simply put, GRU is a variant of LSTM that reduces the network's complexity while maintaining its effectiveness in handling sequential and time series data and based previous sentence GRU's computation and training times are faster. This makes it well-suited for real-time financial prediction environments. In recurrent neural networks like GRU, the main goal is to minimize prediction errors through an optimization process. This is achieved by repeatedly updating the model's weights using the backpropagation through time algorithm [13].

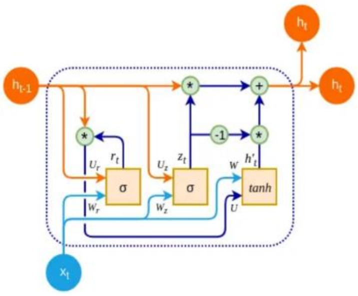

Figure 1. GRU Architecture

Figure 1 shows the architecture of the GRU, which has two gates: the reset gate and the update gate [11]. The reset gate controls how much of the previous information is passed to the next stage, while the update gate determines how much information is updated or retained. The combination of these two gates makes the GRU more effective in capturing temporal information from the data without the need for a complex gate structure [11].

The Gated Recurrent Unit (GRU) architecture includes the update gate, which regulates how much information from the previous hidden state should be carried forward to the current time step. It takes both the previous hidden state and the current input as inputs, generating a value between 0 and 1 that indicates the proportion of information to retain. This gating mechanism helps address the vanishing gradient problem commonly faced in traditional RNNs, allowing better handling of long-term dependencies [14]. The formula for calculating the Update Gate can be expressed as follows.

$$z_t = \sigma\left(w_z * [h_{t-1}, x_t]\right) \quad (1)$$

Where :

z_t : Update Gate $\quad$ w_z : The weight for calculating the update gate

σ : Sigmoid activation $\quad$ h_{t-1} : Hidden state at the previous time step

x_t : Input at time t

The reset gate in a GRU determines how much information from the previous hidden state should be discarded. It generates a value between 0 and 1, where values closer to 0 reduce the influence of past information, while values near 1 retain more. By selectively ignoring parts of the hidden state, the reset gate allows the network to focus on newer, more relevant input data. This mechanism enables the network to concentrate on new, more relevant data while filtering out older information that may no longer be useful [14]. The formula for calculating the Reset gate can be expressed as follows.

$$r_t = \sigma\left(w_r * [h_{t-1}, x_t]\right) \quad (2)$$

Where :

r_t : Reset Gate

w_r : Weight for calculating the Reset Gate

The candidate state, as shown in Equation 3 is responsible for computing the hidden state at the current time step. It is generated using the hyperbolic tangent function (tanh) applied to a combination of the current input and the previous hidden state, modified by the reset gate. This adjustment ensures that only relevant past information influences the current state. The candidate state represents an initial snapshot of the next hidden state before it is updated by the update gate [14]. The formula for calculating the candidate state can be expressed as follows.

$$\widetilde{h_t} = \tanh\left(W * [r_t * h_{t-1}, x_t]\right) \quad (3)$$

Where :

$\widetilde{h_t}$: Candidate State $\quad$ W : Weight for calculating the Candidate State

tanh : Tangent activation

The hidden state in a GRU represents the output at the current time step and is passed to the next GRU unit. It is computed by blending the candidate state and the previous hidden state, with the update gate controlling their contributions. This balance allows the hidden state to retain essential information from both the past and the present, making it more relevant for future predictions. By integrating the update gate, reset gate, and candidate state, GRUs capture long-term information more effectively than traditional RNNs [14]. The formula for calculating hidden state can be expressed as follows.

$$h_t = (1 - z_t) * h_{t-1} + z_t * \widetilde{h_t} \tag{4}$$

Where :

h_t : Hidden State

2.1.2 Value at Risk

Value at Risk (VaR) is a crucial approach in financial risk measurement, as it allows for the calculation of the maximum potential loss that can occur within a specific time frame at a given confidence level, assuming normal market conditions [10]. In the context of financial management, VaR is used to provide a quantitative estimation of the risks that may be faced by a portfolio or individual asset.

Historical simulation is a non-parametric method for calculating Value at Risk (VaR), which directly utilizes past stock data to assess risk without relying on specific statistical distribution assumptions [8]. The primary advantage of this method lies in its ability to avoid assuming that asset return values follow a normal distribution or exhibit linear relationships. The formula for calculating historical simulation can be expressed as follows.

$$VaR = V_0 \text{ x } P_\alpha \text{ x } \sqrt{t} \tag{5}$$

Where :

VaR : Potential loss

V_0 : Initial value magnitude

P_α : Percentile of -α

$\sqrt{t}$: Period

In this approach, the more historical data used, the more accurate the calculated Value at Risk (VaR) becomes [15]. The calculation, as shown in Equation (5), adjusts for both the scale of the initial investment and the time horizon. , with the determined percentile reflecting the desired confidence level. This percentile can be calculated using the following equation :

$$P_\alpha = a \text{ x } n \tag{6}$$

Where :

n = Data quantity

a = Significance level

In Equation (6), this percentile is calculated to represent the maximum potential loss within the specified confidence level.

2.1.3 Model Evaluation

In the final stage, the performance of the GRU model will be evaluated using the MAPE metric. This metric is chosen because it provides valuable insights into how well the model predicts stock prices and measures risk. MAPE offers a clear understanding of prediction errors. The equation for MAPE is as follows [11].

$$MAPE = \sum_{t=1}^{n} \left| \frac{y_i - \hat{y}_i}{\hat{y}_i} \right| \text{ x } 100\% \tag{7}$$

Explained :

n : Sum of the data

$\tilde{y}_i$: Predicted value

y_i : Actual historical value

Mean Absolute Percentage Error (MAPE) measures the performance of a model in making predictions using percentage values. In its classification, the value of MAPE can be categorized as follows [11].

Table 1 MAPE Classification

Range MAPE	Classification
<10%	Very Good
10 – 20 %	Good
20 – 50%	Decent
>50%	Bad

As shown in Table 1, which classifies MAPE, parameter optimization techniques were applied during model training to achieve optimal performance. Key parameters, including the number of GRU units, learning rate, batch size, and window size, were systematically adjusted to improve the model's predictive accuracy. These optimized parameters significantly contributed to reducing the MAPE value, ensuring that the GRU model is both accurate and reliable.

2.2 Research Methodology

Figure 2 outlines the research process, beginning with dataset preparation (collection, preprocessing, and EDA), splitting data into training and test sets, and normalizing with min-max scaling. The GRU algorithm is trained on the training data, with model selection based on MAPE. Stock predictions are then used in historical simulation to estimate Value at Risk (VaR).

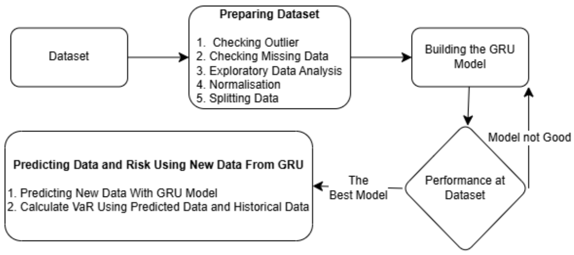

Figure 2 Overral prediction process

The case study focuses on ICBP stock, part of Indofood, a major player in the food sector with high market capitalization, liquidity, and trading activity. The research uses data from July 1, 2019, to July 31, 2024, with the close price as the sole variable. The variables to be used are outlined in Table 2 of the study.

Table 2 Variable in Dataset

Variable	Description
Close Price	This variable represents the final price at which a stock is traded during a given trading day.

The research methodology, as illustrated in Figure 2, is designed to follow a structured, systematic, and iterative process that ensures each step is interconnected and contributes to the overall objective of producing accurate predictions and reliable risk assessments. This approach emphasizes a clear workflow, starting from the preparation of the dataset to the development of the predictive model and the integration of risk analysis.

2.2.1 Preparing Dataset

In data preprocessing, outliers and missing values will be addressed to ensure quality. Outliers, identified as unusual price spikes, will be investigated for accuracy. Exploratory Data Analysis (EDA) will follow, using time series graphs to analyze trends and seasonal patterns in ICBP stock's historical closing prices. The data, consisting of dates and closing prices, will be visualized using Matplotlib line charts to observe price changes over time. Further preprocessing includes normalizing the data to a 0-1 range using min-max scaling and will be split into training and testing subsets with an 80:20 ratio. The Min-Max Scaler can be calculated using the following formula [11].

$$X_{Scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{8}$$

Explained

X_{Scaled} : Normalized data result X_{min} : Minimum value of the dataset
X : Original data value X_{max} : Maximum value of the dataset

2.2.2 Building Building the GRU Model

This study involves constructing a GRU model using a layered architecture, with key parameters like the number of units per layer, learning rate, batch size, and window size optimized for performance. Dropout is applied to prevent overfitting, and a dense layer processes GRU outputs into predictions for risk assessment against test data. The number of units in each GRU layer is critical for capturing data patterns. While more units enhance the model's learning capacity, they can lead to overfitting if the model becomes overly complex for the dataset. Therefore, the number of units is often adjusted through experimentation to strike a balance between learning capacity and generalization.

2.2.3 Model Performance at Dataset

This stage evaluates the performance of the developed GRU model using various optimizers and previously tested neuron configurations to identify the optimal architecture. Model performance will be assessed using the Mean Absolute Percentage Error (MAPE), chosen for its effectiveness in measuring predictive accuracy by quantifying percentage errors relative to actual values. MAPE was selected as it provides an interpretable error metric suitable for the data characteristics in this study. The evaluation results, derived from test data, will be compared to determine the best-performing GRU structure based on the applied parameter optimization process.

2.2.4 Predicting Data and Risk Using New Data From GRU

The GRU model that has been developed and achieved the best MAPE value will be utilized to predict new data and evaluate potential risks based on the prediction results. Before conducting the risk analysis, stock returns must first be calculated using the following formula:

$$Rt = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{9}$$

Where :

Rt : Return at time *t* P_{t-1} : Stock price at the previous time step
P_t : Stock price

This study calculates the maximum potential loss by combining GRU model predictions with historical data from the testing period to compute Value at Risk (VaR) using historical simulation. This approach improves VaR accuracy and provides a more comprehensive risk analysis of ICBP stock.

3. RESULTS AND DISCUSSION

3.1 Preparing The Dataset

PT Indofood Sukses Makmur Tbk, a leading entity in the food sector, was selected for this study due to its large market capitalization, significant role in Indonesia's economy, high liquidity, and active trading frequency, making it a strong representation of blue-chip stock performance during the study period from July 1, 2019, to July 31, 2024. During data preparation, outliers were identified to distinguish input errors from genuine market events, with results indicating no outliers as price movements remained within reasonable bounds. Missing values were checked using Python's pandas library, specifically the isnull() function, which confirmed no missing data, ensuring the dataset's completeness and reliability for analysis.

Figure 3 ICBP Closing Price

The visualization of ICBP's stock based on figure 3 closing price movements from 2019 to 2024 reveals significant fluctuations. In early 2020, the chart shows a strong upward phase, reaching a peak at around the 12,000 level, followed by a sharp decline until early 2021 when prices dropped to approximately 8,000. The period from 2022 to 2023 is characterized by a more stable upward trend, with prices gradually returning to the 11,000 level before entering a stable phase in mid-2024. During this period, price movements were more constrained, fluctuating between the 10,000 and 12,000 levels. Overall, the trend transitions from a downward phase (2019–2021) to an upward phase (2022–2023) but shifts into a consolidation pattern by 2024.

Table 3 Statistic Descriptive of Dataset

Statistic Descriptive							
Count	Mean	Std	Min	25%	50%	75%	Max
1236.0	9880.18	1179.61	7100.00	8800.00	10025.00	10850.00	12400.00

Based on Table 3, which details ICBP stock prices from July 1, 2019, to July 31, 2024, the average stock price during this period was 9,880.18, with a standard deviation of approximately 1,179.61 around the mean. Most stock prices fell between 8,800 (the first quartile) and 10,850 (the third quartile), indicating that the majority of price movements remained stable within this range. The median stock price was 10,025, suggesting that half of the prices were below this value, and the other half were above it. Overall, ICBP's stock prices during this period were relatively stable, with fluctuations that remained predictable.

The data will undergo min-max normalization to align variable scales and prevent dominance by specific values. String values will be converted to numeric (float), followed by re-normalization for consistency. The normalized data will then be split 80:20 into training (July 1, 2019–July 27, 2023) and testing (July 28, 2023–July 31, 2024) sets. Table 4 and Table 5 show the normalized train and test results.

Table 4 Normalization Result of Train Data

Period	**Close Price**
July 01, 2019	0.57075472
July 02, 2019	0.57075472
:	:
July 27, 2023	0.76886792

Table 5 Normalization Result of Test Data

Period	Close Price
July 28, 2023	0.77358491
July 31, 2023	0.77358491
:	:
July 31, 2024	0.71698113

3.2 Building the GRU Model

A GRU model will be built with a layered architecture, optimizing units, learning rate, batch size, and window size. Using historical ICBP stock data, it will predict daily closing prices with a 40-point window size, representing about two months for capturing short-term trends.

Table 6 GRU Structure

GRU Model	
GRU	(64, Return Sequence TRUE)
Dropout	(0.1)
GRU	(64, Return Sequence TRUE)
Dropout	(0.1)
Dense	(8, Relu)
Dense	(1, Linear)

The GRU model in Table 6 predicts stock prices by integrating key indicators of closing price movements. It begins with a GRU layer of 64 units, set to return sequences for processing time-series data, and includes a 0.1 dropout rate to reduce overfitting. By setting *return_sequences=True*, this layer outputs a sequence of data for each time step, enabling subsequent layers to process time-series information further. A second GRU layer with 64 units refines temporal relationships, followed by another 0.1 dropout layer for added regularization. The model concludes with a Dense layer of 8 units using ReLU activation to compact features and a final Dense layer with 1 unit and linear activation for stock price predictions.

The choice of a GRU architecture with two layers of 64 units each is based on the need to balance accuracy and training efficiency. The selection of 64 units was guided by prior research findings [16], which emphasize that this configuration offers sufficient capacity for capturing temporal patterns in the data without introducing excessive complexity. Using a higher number of units could lead to marginal accuracy improvements while significantly increasing the computational cost and risk of overfitting. Additionally, a Dropout rate of 0.1 was applied to mitigate overfitting by randomly deactivating 10% of the neurons during training, promoting better generalization of the model [16]. This architecture was designed to ensure a balance between accuracy, training speed, and model robustness.

3.3 Model Performance at Dataset

The model will be trained using Adam, SGD, and RMSprop optimizers with epochs=45 and batch_size=64. Performance will be evaluated using MAPE to identify the most effective optimizer for stock price prediction.

Table 7 Predicted Result of All Optimizer

Period	Test Data	Adam	SGD	RMSProp
July 28, 2023	11200	11132	11291	11257
July 31, 2023	11200	11144	11242	11233
:	:	:	:	:
July 31, 2024	10925	10824	10779	10905

Based on Table 7, the Adam optimizer consistently produces predictions closer to the actual test data compared to SGD and RMSProp, making it more effective in capturing patterns and providing accurate results. Based on previous research by Faisal Mehmood [17] Adam offers faster convergence and effective handling of noisy data due to its combination of momentum and adaptive learning rates, though it can struggle with generalization and be computationally expensive. SGD is simple, efficient for large datasets, and stable for convex problems but can be slow for complex datasets and unstable with noisy gradients. RMSProp adjusts learning rates based on recent gradients, making it suitable for non-stationary problems while controlling oscillations, though it can sometimes converge too quickly to suboptimal solutions.

The conclusion that Adam performs best in this context is further supported by the Mean Absolute Percentage Error (MAPE) analysis, which will be detailed in Table 8.

Table 8 Model Performance in MYOR

Optimizer	**Adam**	**SGD**	**RMSProp**
MAPE	1.29	1.57	1.36

The evaluation in Table 7 indicates that Adam achieved the best performance across all metrics, with the lowest MAPE of 1.3%. In comparison, RMSprop demonstrated moderate performance, with a higher MAPE of 1.4%. SGD performed the worst, with the highest error rate on the MAPE metric at 1.6%, indicating lower accuracy and higher variability in predictions. The Adam model performance compared to actual data is illustrated in Figure 4.

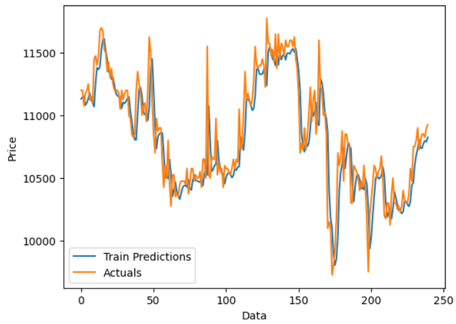

Figure 4 Model Performance on Actual ICBP Data

3.4 Predicting Data and Risk Using New Data From GRU

Table 9 presents the predicted stock prices of ICBP using the GRU model, this predicted data and the test data will be combined to calculate the Value at Risk (VaR) using a 5-day historical simulation at a 95% confidence level and based on a single asset valued at 1 million Rupiah. The selection of a 5-day holding period is based on price predictions using the GRU model, which covers the next 5 days. Meanwhile, the choice of the confidence level is based on previous research comparing variance-covariance calculations with historical simulation. The research found that a 95% confidence level performs better for the historical simulation method [15].

Table 9 New Data in ICBP Stock for 5-Day

Period	**New Data (IDR)**
August 01, 2024	10824
August 02, 2024	10802
August 03, 2024	10772
August 04, 2024	10743
August 05, 2024	10716

The percentage change in asset prices between periods is calculated to derive the return before calculating the Value at Risk (VaR) using Equation (5). This return data, summarized in Table 10, is used to determine the worst-case return within the bottom 5% of the historical return distribution. In this study, the 5th percentile value is approximately 0.0242, representing the threshold for potential losses. In the calculation, the P_α Value is adjusted for the holding period by multiplying it with the square root of time. For a 5-day holding period square root of time equals approximately 2.236, reflecting the cumulative risk over the forecast horizon. The Calculated Value at Risk represents the maximum expected loss for the ICBP asset over a 5-day period with 95% confidence.

Table 10 Return Dataset

Period	Price (IDR)	Return
July 18, 2019	11750	0.008547
July 20, 2019	11475	-0.023682
:	:	:
August 05, 2024	10716	-0.002582

The risk analysis for the single asset yields an estimated Value at Risk (VaR) of IDR 65.785. This value indicates that, with a 95% confidence level, the maximum expected loss over the next 5-day period will not exceed IDR 65.785. This VaR estimate is derived through a combination of historical data and predictive data for the next 5 days generated by the Gated Recurrent Unit (GRU) model. This method is expected to provide a more informative risk estimate, which is relevant for decision-making in asset risk management.

4. CONCLUSION

This study predicts the price and analyzes the risk of PT Indofood Sukses Makmur Tbk (ICBP) using the Value at Risk (VaR) approach through historical simulation, integrating historical data with a GRU-based predictive model to capture stock price patterns. At a 95% confidence level, the VaR estimate indicates a maximum potential loss of IDR 65.785 over the next 5 days under normal market conditions. By incorporating GRU predictions, the approach enhances risk estimates with future price forecasts, offering valuable insights for asset risk management in dynamic market conditions. Future research could explore incorporating alternative data sources such as macroeconomic indicators, and expanding risk metrics to provide a more comprehensive risk assessment. Additionally, validation of the Value at Risk (VaR) results can be considered to ensure the accuracy and reliability of the risk estimates.

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