Comparative Analysis of Deep Learning LSTM and Prophet Models in Predicting Victori Self Service Sales Trends

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Abstract
Sales forecasting is a crucial aspect of operational planning in the retail business, as it helps companies manage inventory, design promotional strategies, and optimize supply chains. This study compares the performance of two time series forecasting methods, namely Long Short-Term Memory (LSTM) and Prophet, in predicting daily sales trends at Victory Swalayan during the period from March 1 to May 30, 2025. The dataset consists of daily transaction records that were aggregated into a daily sales time series. The LSTM model was trained using a multi-step iterative approach with a seven-day input window, while the Prophet model was built using default settings with weekly seasonality and trend components. Model performance was evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) metrics. The results show that the Prophet model achieved higher accuracy than LSTM, with an MAE of 1,342,401 and an RMSE of 1,615,108, while LSTM recorded an MAE of 1,986,710 and an RMSE of 2,502,594. Therefore, Prophet is more effective in modeling seasonal patterns and daily sales trends in retail business data.

Keywords: Sales Forecasting, Time Series, LSTM, Prophet, Model Evaluation, Daily Retail

Introduction

Sales forecasting plays a vital role in the retail business as it supports operational efficiency and strategic decision-making. Accurate estimates help manage stock to avoid shortages or excesses. In addition, sales forecasting allows for more targeted promotional planning and more measurable financial management, including budgeting and projecting cash flow. This information is also the basis for determining pricing policies, product expansion, and distribution strategies. With good forecasting, companies can be more responsive to market changes and optimize the overall supply chain. One of the common techniques used in sales forecasting is data mining, which is the process of extracting hidden information or patterns from large data sets [1]. In the context of retail, data mining allows companies to analyze historical sales data to identify trends, seasonal patterns, and recurring consumer behavior.

Data mining is the process of extracting meaningful information or patterns from large data sets using statistical, mathematical, and artificial intelligence techniques. [2], [3], [4], [5], [6], [7]. The goal is to find hidden relationships, trends, or specific patterns that are not directly visible from the raw data [8], [9], [10], [11], [12], [13]. This analysis uses two data mining algorithms for time series forecasting on daily sales data of Victory Supermarket Pangkalan Berandan, namely *long short-term memory* (LSTM) and Prophet. LSTM is a recurrent artificial neural network that is effective in capturing complex patterns and long-term relationships in sequential data [14], [15], [16]. Meanwhile, Prophet is an open-source package developed by the *Facebook Data Science team* for time series forecasting based on additive models [17]. This model is designed to handle data with strong seasonal patterns, able to accommodate missing data, trend changes, and holiday effects [18], [19]. The comparison of the two aims to assess the effectiveness of the model in predicting daily sales in the retail sector. Victory Swalayan is a retail company engaged in shops and supermarkets, located at Jl. Mesjid No. 60, Brandan Timur Baru, Babalan, Langkat, North Sumatra. Located in Pangkalan Brandan, this supermarket serves the daily needs of the community and is an important part of local retail distribution.

Several previous studies have shown that the LSTM model excels in modeling complex and nonlinear data, such as in predicting sales with sharp fluctuations. On the other hand, the Prophet method is considered effective in predicting data with strong seasonal patterns, such as weekly or monthly sales. One study by Feliana Oktavia and Arita Witanti (2024) showed that the LSTM model produced better predictions than GRU in forecasting gold prices. The best LSTM results were shown with an MAE value of 0.0389, RMSE 0.0475, and MAPE 5.2047% [19]. Meanwhile, research by Pablo Negre et al. (2024) showed that the Prophet model excels in predicting total annual sales of seasonal footwear, with an accuracy of 98.8% and an MAE of 158.8 [20].

The purpose of this analysis is to evaluate the performance of LSTM and Prophet models in predicting daily sales trends at Victory Swalayan Pangkalan Berandan. The focus of the study includes prediction accuracy, ease of implementation, and interpretability of results. By comparing the two models, it is expected to gain insight into the most effective forecasting method to support data-based business decision making.

Research methodology

The proposed research stages can be seen in Figure 1 below:

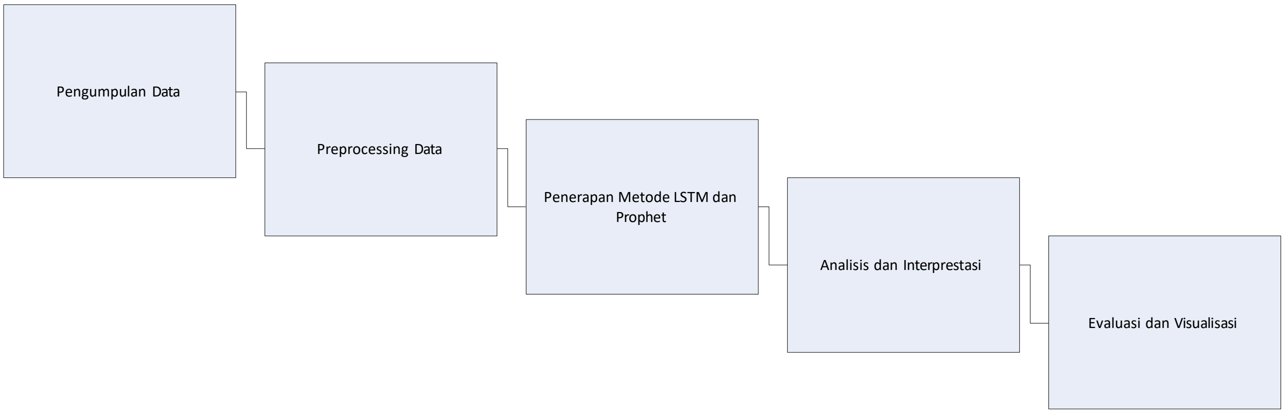

Figure 1. Research Stages

1. **Data collection**

This stage uses daily transaction data from Victory Swalayan during the period of March 1 – May 30, 2025 (91 days). The initial dataset contains transaction details such as invoice date, product category, product code, quantity sold (QtyJual), and price per unit. This data is then processed into a daily sales time series by summing the total sales per date.

2. **Data Preprocessing**

Next, the raw data is cleaned and processed through several stages. First, all transactions are converted into an aggregate form in the form of total sales per day in Rupiah units. After that, a check is carried out to ensure that there are no missing dates in the time range from March 1 to May 30, 2025, so that each day has a sales value. Furthermore, the sales data is normalized for LSTM modeling purposes so that the training process is more stable and faster. Then, the data is divided into two parts: training data covers the period from March to April 2025 (a total of 61 days), while test data covers the month of May 2025 (30 days). This separation is done *out-of-sample* , meaning that the test data is not included in the model training process and is only used to measure prediction performance.

3. **Implementation of LSTM and Prophet Methods**

The next stage is the LSTM Model built using Keras (TensorFlow) with a single LSTM layer architecture and one Dense output layer. The model input is a window of sales data from the previous seven days, using the Adam optimizer and the MSE loss function. Predictions are made in stages over the next 30 days using an iterative multi-step approach. Meanwhile, the Prophet model is built with the default configuration, which automatically identifies weekly trends and seasonality. The model is trained on March–April 2025 data and used to predict daily sales in May, focusing on the median predicted value without including external variables.

4. **Analysis and Interpretation**

The predicted results of both models are compared with the actual data for May 2025. The analysis is carried out to assess the extent to which the models are able to follow the trends and seasonal patterns present in the test data.

5. **Evaluation and Visualization**

Model performance is evaluated using two main metrics, namely *Mean Absolute Error* (MAE) and *Root Mean Squared Error* (RMSE). MAE measures the average absolute error between predicted and actual values, while RMSE calculates the root of the mean squared of these differences.

LSTM Deep Learning Model

Long Short-Term Memory (LSTM) is an artificial neural network architecture belonging to *the Recurrent Neural Network* (RNN) family, designed to handle sequential or time series data. LSTM was developed to overcome the limitations of standard RNNs, especially the vanishing gradient problem that makes it difficult for RNNs to remember information over long periods of time. LSTM has a special structure consisting of three main gates, namely *forget gate, input gate, and output gate* , which function to regulate the flow of information into, stored, and out of the memory unit. With this ability, LSTM is very effective in modeling long-term relationships in complex and nonlinear data. Therefore, LSTM is often used in various applications such as price prediction, sales, weather, as well as in the fields of natural language processing and other sequential data. The following is a general formula for the LSTM model that explains how data is processed at each time step:

1. ***Forget Gate:***

$$\boldsymbol{ft = \sigma(Wf \cdot [h\{t-1\}, xt] + bf)}$$

2. ***Input Gate:***

$$\boldsymbol{it = \sigma(Wi \cdot [h\{t-1\}, xt] + bi)}$$

3. ***Cell State Candidates:***

$$\tilde{C}\boldsymbol{t} = \boldsymbol{tanh}(\boldsymbol{W}C \cdot [\boldsymbol{h\{t-1\}, xt}] + \boldsymbol{b}C)$$

4. ***Cell State Update:***

$$C\boldsymbol{t} = \boldsymbol{ft} * C\{\boldsymbol{t-1}\} + \boldsymbol{it} * \tilde{C}\boldsymbol{t}$$

5. ***Output Gate:***

$$\boldsymbol{ot = \sigma(Wo \cdot [h\{t-1\}, xt] + bo)}$$

6. ***Hidden States:***

$$\boldsymbol{ht = ot * tanh}(C\boldsymbol{t})$$

Information:

xt	: input at time t
h{t-1}	: hidden state at previous time
Ct	: cell state (internal memory) at time t
ft, it, ot	: output from *forget gate, input gate, and output gate*
$\tilde{C}$ t	: new cell state candidate
σ	: sigmoid activation function
tanh	: tanh activation function
W and b	: weights and biases of the model

Prophet

Prophet is a time series forecasting method *developed* by Facebook (Meta). This method is designed to be easy to use, flexible, and able to provide accurate prediction results, especially on data with seasonal patterns, non-linear trends, and holidays or special days. Prophet works based on an additive model approach where the time series components are separated into three main parts, namely Trend (g(t)) long-term changes in data and Seasonality (s(t)) recurring patterns such as daily, weekly, or annual seasons. And Holiday effect (h(t)) the effect of holidays or special events.

The Prophet model can be written in the form of a general equation:

$$\boldsymbol{y(t) = g(t) + s(t) + h(t) + \varepsilon\_t}$$

Where:

y(t) : predicted value at time t

g(t) : trend component
s(t) : seasonal component
h(t) : holiday or special day component
ε_t : random error (error term)

1. Trend Component (g(t))

Prophet supports two types of trends: *Piecewise Linear* : trends with multiple changepoints *and* Logistic *Growth* : growth trends limited by a maximum capacity.
Piecewise Linear Trend Formula :

$$g(t) = (k + a(t)^T \delta)t + (m + a(t)^T\gamma)$$

Information:
k : initial rate (slope)
m : initial intercept
a(t) : change point indicator at time t
δ : change in rate (impact of each changepoint)
γ : change in intercept due to changepoint

2. Seasonal Component (s(t))

Seasonality is modeled using a Fourier series:

$$s(t) = \sum_{n-1}^{N} [a_n \cos (\frac{2\pi nt}{P})] + b_n \sin (\frac{2\pi nt}{P})$$

Information:
P : seasonal period (e.g. 365 for annual seasonal)
N : number of Fourier components
a_n, b_n : coefficients learned during training

3. Holiday Component (h(t))

Holidays are modeled as binary indicator effects for specific dates:

$$h(t) = \sum_{i-1}^{L} \lambda \mathrm{iDi}(t)$$

Information:
Di(t) : indicator of whether the i-th holiday occurs at time t
Λi : impact of the i-th holiday

4. Error Component (ε_t)

The error or residual is assumed to be independent white noise:

$$\varepsilon_t \sim N(0, \sigma^2)$$

Results and Discussion

This study uses daily transaction data from Victory Supermarket during the period from March 1 to May 30, 2025, with a total of 91 days of observation. The initial dataset contains detailed transaction information including invoice date, product category, product code, quantity sold (QtyJual), and price per unit. The data is then processed into a daily sales time series by summing the total sales per date. The results of this aggregation are then used as input for a time series-based forecasting model.

Table 1. Sample Data

Name category	No invoice	Date invoice	Code product	Name product	Qty sell	Price ual
Baby soap	P2025/03/0 00001	2025-03-01 08:10:01	1440	Jb milk rice bath 400ml pouch	1	31650
Milk	P2025/03/0 00002	2025-03-01 08:43:28	4626	Dancow instant fortigro 195g	1	26750

Tissue	P2025/03/0 00003	2025-03-01 09:01:55	885	Softpack montiss 185's	1	6480
Detergent	P2025/03/0 00004	2025-03-01 09:07:49	4799	Daia detergent powder violet passion baseq 4kg	1	72430
Detergent	P2025/03/0 00004	2025-03-01 09:07:49	6309	Rinso automatic liquid 4.5l	2	78000
Floor cleaner	P2025/03/0 00004	2025-03-01 09:07:49	4396	Soklin purple floor bottle 900ml	3	15169
Air freshener	P2025/03/0 00004	2025-03-01 09:07:49	3877	Dahlia air freshener cherry blossom	2	11060
Air freshener	P2025/03/0 00004	2025-03-01 09:07:49	1372	Glade ofa peony & berry ref 70g	5	11688
Air freshener	P2025/03/0 00004	2025-03-01 09:07:49	3141	Stella all in one jasmine 42+13gr	4	10550
Detergent	P2025/03/0 00005	2025-03-01 09:15:49	6164	Soklin liquid detergent soft jumbo sct 6+1	1	5820
Accessories	P2025/03/0 00006	2025-03-01 09:40:03	7532	Hair tie donut tube feather	1	9000
Body mist	P2025/03/0 00006	2025-03-01 09:40:03	1692	Iz bms korean nami 100	1	18034
Body mist	P2025/03/0 00006	2025-03-01 09:40:03	1695	Iz bms true love 100	1	18034
Conditioner	P2025/03/0 00006	2025-03-01 09:40:03	2219	Sunsilk con blk shine 160ml	1	31338
Key chain	P2025/03/0 00006	2025-03-01 09:40:03	6527	Kuromi rubber keychain	1	5500
Hair net	P2025/03/0 00006	2025-03-01 09:40:03	6449	Hair net	1	2250
Hairpin	P2025/03/0 00006	2025-03-01 09:40:03	7885	Hair net flower clip	1	24500
Facial cotton	P2025/03/0 00006	2025-03-01 09:40:03	3957	Selection cotton 100 g	1	12000
Haircut	P2025/03/0 00006	2025-03-01 09:40:03	6454	Bop lidi kep	1	4000
…..	…...	…..	…..	……	…..	…..
shampoo	p2025/05/0 06860	2025-05-30 22:04:00	9017	zinc shampoo refreshing cool 12scht 10ml	1	5800

Deep Learning LSTM Model Testing

The LSTM model is built using Keras (TensorFlow) with a single LSTM layer architecture and one Dense output layer. The model input is a window of sales data from the previous seven days, using the Adam optimizer and the MSE loss function. Predictions are made in stages over the next 30 days using a multi-step iterative approach.

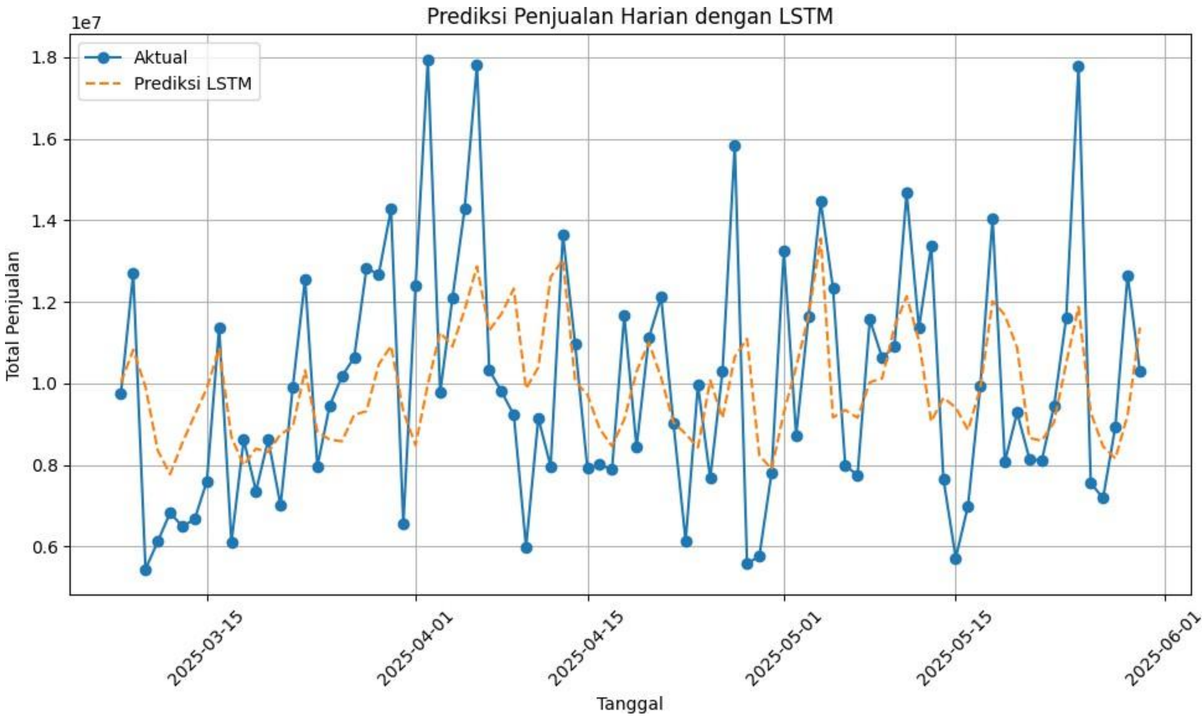

Figure 2. Daily Sales Prediction Results of the LSTM Method

Figure 2 shows the results of daily sales prediction using the LSTM model at Victory Supermarket during the period from March 1 to May 30, 2025. The graph compares the actual values and the predicted results in the form of a time series. The horizontal axis represents the transaction dates during the 91 days of observation, while the vertical axis shows the total daily sales in rupiah (with an exponential scale of 1e7). The dotted blue line depicts the actual data that shows high fluctuations and seasonal patterns, while the dashed orange line represents the predicted results from the LSTM model. In general, the LSTM model is able to capture seasonal trend patterns in the data, although there are deviations at extreme points, such as sudden spikes or drops. This model produces smoother predictions and tends not to fully follow the highly volatile actual values. This indicates that LSTM is effective in modeling general patterns and short-term trends, but is less responsive to sharp variations caused by external factors such as promotions or holidays.

Probhet Model Testing

The Prophet model was tested using daily sales data of Victory Supermarket for the period from March 1 to May 30, 2025. Historical data that has been processed into an aggregate time series per day is used as the main input.

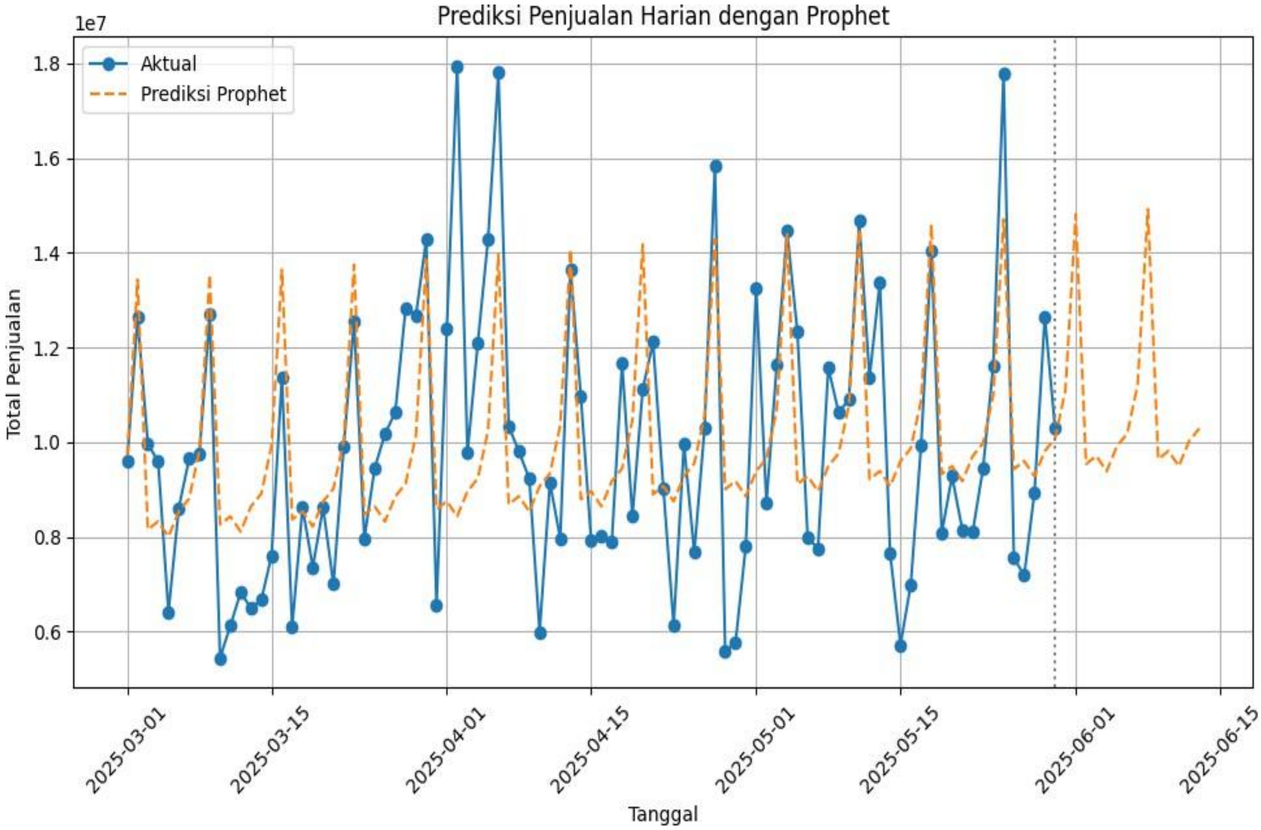

Figure 3. Daily Sales Prediction Results Using the Prophet Method

Figure 3 shows the results of Victory Supermarket's daily sales prediction using the Prophet model for the period March to May 2025. The graph compares actual and predicted data in a time series format, with the horizontal axis representing the transaction date and the vertical axis showing the total daily sales in rupiah (exponential scale 1e7). The dotted blue line depicts the actual data, while the dashed orange line shows the Prophet prediction results. The Prophet model is able to capture weekly seasonal patterns consistently, as seen from the similarity of the peak and valley rhythms between the actual and predicted data. However, this model produces a prediction pattern that is periodic and tends to be symmetrical, making it less adaptive to sudden fluctuations or spikes in sales that do not repeat regularly. This can be seen from the fairly large differences at several extreme points. Overall, the Prophet prediction is relatively stable and quite representative in describing daily seasonal trends, so it can be used for stock planning and operational strategies. The dashed vertical line marks the boundary between the March - April training data and the May 2025 prediction period. Because it does not use external variables such as promotions or holidays, the Prophet projection better reflects normal conditions based on historical trends.

Model Evaluation

The evaluation was conducted to assess the level of accuracy and effectiveness of the model in predicting daily sales based on historical data of Victory Swalayan. In this study, two time series modeling approaches, namely *Long Short-Term Memory* (LSTM) and Prophet, were compared quantitatively against actual data to measure the predictive performance of each model. The assessment of model performance is based on three evaluation metrics commonly used in the time series prediction literature, namely *Mean Absolute Error* (MAE), *Root Mean Square Error* (RMSE), and *Mean Absolute Percentage Error* (MAPE). MAE is used to measure the average absolute error between the actual value and the predicted value, RMSE is used to provide a greater penalty for large errors, while MAPE expresses the error in percentage terms of the actual value. The use of these three metrics provides a comprehensive evaluation approach in measuring the deviation between prediction and realization. The evaluation results not only provide an overview of the predictive accuracy of each model, but also become the basis for determining the most appropriate model for use in the context of seasonal and fluctuating retail sales forecasting.

Table 2. Model Evaluation Results

Model	**MAE (Rp)**	**RMSE (Rp)**
Prophet	1,342,401	1,615,108
LSTM	1,986,710	2,502,594

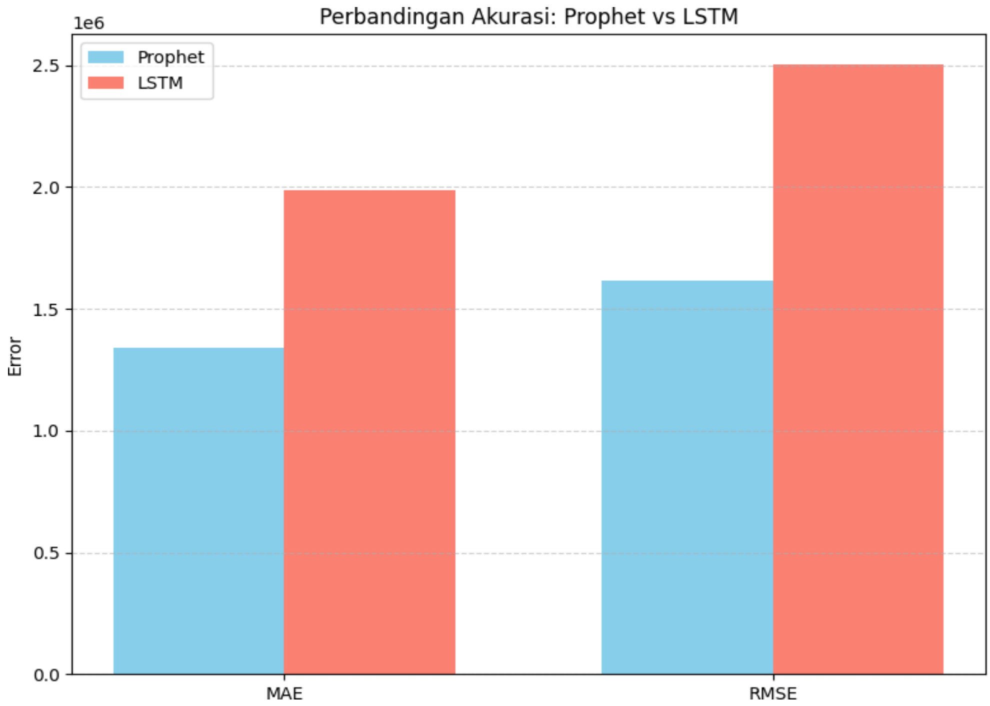

Figure 4. Comparison of Model Evaluation

Figure 4 shows a comparison of the accuracy of the Prophet and LSTM models based on the MAE and RMSE metrics. Prophet produces lower MAE and RMSE values than LSTM, which are ± 1,342,401 and ± 1,615,108. While LSTM recorded MAE ± 1,986,710 and RMSE ±2,502,594. These results indicate that Prophet is more accurate and stable in predicting Victory Supermarket daily sales compared to LSTM.

Conclusion

Based on the results of the analysis and evaluation that have been carried out, it can be concluded that the Prophet model has a better performance than the LSTM model in predicting daily sales of Victory Swalayan during the period March to May 2025. Prophet shows superior ability in capturing consistent weekly seasonal patterns and general sales trends, with evaluation results showing an MAE value of 1,342,401 and an RMSE of 1,615,108. Meanwhile, the LSTM model produces an MAE value of 1,986,710 and an RMSE of 2,502,594, which indicates a higher prediction deviation from the actual data. This indicates that Prophet is more effective in handling retail sales data with regular seasonal patterns, even without considering external variables. On the other hand, LSTM tends to produce more volatile and less accurate predictions for stable sales patterns. Therefore, in the context of short-term sales prediction for retail business data with seasonal characteristics such as Victory Supermarket, the Prophet model is more recommended as an analytical tool to support more targeted operational decision-making, stock management, and marketing strategies .

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