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Predicting Time Series Sales Transaction Value at E-Stall Crunchy Merchants Using Long-Short-Term Memory

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Abstract
The utilization of sales data as a foundation for strategic decision-making plays a crucial role in supporting the operational success of Merchant E-Stall Crunchy. However, the high variability and volume of daily transaction data create challenges in accurately identifying sales patterns. To address this issue, this research proposes the application of a deep learning approach—Long Short-Term Memory (LSTM)—to perform time series–based prediction of sales transaction values. The objective of this study is to develop a predictive model capable of uncovering historical patterns, seasonal trends, and demand fluctuations, thereby providing insights that support managerial decision-making. The Design Science Research methodology is employed, covering problem identification, model development, implementation, and evaluation. The dataset consists of daily sales transactions from E-Stall Crunchy, including transaction dates, product types, and sales values. The LSTM model is implemented to predict daily transaction values, and its performance is evaluated using MAE and RMSE metrics. The expected outcome includes an accurate prediction model and analytical recommendations that can support strategies for improving sales performance and operational efficiency.

Keywords: Time Series, Sales Prediction, LSTM, Deep Learning, E-Stall Crunchy.

1. Introduction

The digital transformation of the food and beverage industry has accelerated rapidly in recent years, driven by the widespread adoption of online food delivery platforms such as GoFood, GrabFood, ShopeeFood, and MaximFood (Achmad et al., 2025). These platforms have reshaped consumer purchasing behavior by offering convenience, faster service, and broader accessibility. As competition intensifies, merchants operating within this ecosystem are increasingly required to leverage data analytics to understand their business performance and respond effectively to fluctuating market demands. Transaction data, which accumulates on a daily basis, holds strategic value for optimizing sales operations—yet many small and medium merchants still underutilize this information, limiting their ability to make accurate, data-driven decisions (Meitasari and Sinduwiatmo, 2024).

The rapid growth of online food delivery platforms—such as GoFood, GrabFood, ShopeeFood, and MaximFood—has significantly transformed how culinary businesses operate in Indonesia. These platforms enable merchants to receive and manage food orders digitally while improving distribution efficiency and expanding market reach. In this increasingly digital ecosystem, the role of data-driven decision-making has become crucial for sustaining competitiveness and optimizing operational performance (Ahmed et al., 2022).

Modern analytical techniques, particularly machine learning and deep learning, provide powerful tools for understanding sales behavior and predicting future business performance. Predictive modeling has been widely adopted in retail and e-commerce industries to identify sales patterns, reduce uncertainty, and support strategic planning (Vangibhurathachhi, 2025). Deep learning models, especially those designed for sequential data, have shown strong capabilities in capturing temporal dependencies and generating accurate forecasts (Fadillah, 2025).

E-Stall Crunchy, an online culinary merchant located in Jalan Pramuka Lrg. Brantas 1, Pematang Sulur, Kota Jambi, generates a substantial volume of daily transaction data. However, much of this data remains underutilized, often stored as raw logs without deeper analysis. Manual evaluation of sales patterns is time-consuming and prone to inefficiencies, limiting the merchant's ability to make evidence-based decisions. Consequently, the business lacks timely insights into sales fluctuations, demand trends, and revenue opportunities (Santoso et al., 2025).

To address this gap, this research proposes a predictive modeling approach using Long Short-Term Memory (LSTM), a recurrent neural network architecture well-suited for time-series forecasting due to its ability to learn long-term dependencies. By applying LSTM to historical sales transaction data, the study aims to generate accurate predictions of future sales values, enabling the merchant to optimize inventory planning, marketing strategies, and overall business performance. Previous works highlight the effectiveness of LSTM for financial and retail forecasting tasks, reinforcing its relevance for transaction value prediction. This study is expected to contribute both practically and academically: practically by providing E-Stall Crunchy with a data-driven forecasting tool, and academically by demonstrating the application of LSTM for sales transaction prediction in the context of online food merchants in Indonesia (Mojtahedi and Chow, 2025).

2. Literature Review

Time-series forecasting is widely recognized as a critical analytical method for understanding temporal patterns and supporting strategic decision-making in business environments. As organizations increasingly rely on digital platforms, the ability to analyze historical trends and anticipate future outcomes becomes essential for maintaining competitiveness (Wahyuningtyas and Fadil, 2024). The rapid expansion of digital transactions provides vast data streams that demand advanced computational techniques capable of capturing complex time-dependent relationships.

Classical forecasting models such as ARIMA, SARIMA, and exponential smoothing have served as foundational tools in time-series prediction. However, these models are often limited in addressing nonlinear behaviors, sudden fluctuation patterns, and long-term dependencies inherent in modern business data (Ferdowsy, 2024). The limited flexibility of statistical approaches has motivated researchers to explore machine learning and deep learning techniques, which are better suited for handling high variability and dynamic sequences (Ahmed et al., 2023).

Deep learning, particularly through recurrent neural network (RNN) architectures, has demonstrated substantial improvements in forecasting accuracy across diverse domains. Long Short-Term Memory (LSTM) networks, introduced to mitigate the vanishing gradient issue, have become a dominant model for sequential prediction tasks (Yudistira et al., 2023). Research indicates that LSTM effectively captures long-range temporal dependencies, allowing it to outperform traditional RNNs and classical statistical methods in complex environments. In financial forecasting, for example, LSTM has achieved superior performance in predicting stock movements and volatility (Natzir et al., 2025). In industrial applications, LSTM has successfully modeled fluctuating energy demands and sensor-driven datasets that exhibit strong temporal structure.

In the retail and e-commerce sector, deep learning-based forecasting has become increasingly relevant as consumer purchase behaviors grow more dynamic and multidimensional. Several studies reveal

that LSTM-based sales prediction models outperform linear models by effectively learning seasonal spikes, promotional effects, and nonlinear consumption trends (Salsabila, 2020). Accurate forecasting has been shown to enhance inventory management, reduce operational costs, and support demand-driven resource allocation. Furthermore, deep learning models allow businesses to identify customer purchasing patterns, enabling more targeted marketing strategies (Rane et al., 2024).

The digital food-delivery ecosystem—including platforms such as GoFood, GrabFood, and ShopeeFood—presents unique challenges and opportunities for data-driven forecasting. Merchants in this sector generate large volumes of highly variable transaction data influenced by time-of-day effects, weather conditions, consumer habits, and promotional campaigns. Leveraging predictive analytics in the online food industry has been shown to improve service quality, decrease order delays, and optimize menu availability. Studies also highlight that forecasting models support strategic decision-making by helping merchants anticipate demand surges, plan food preparation, and reduce wastage. These benefits are particularly relevant for small and medium-sized food businesses operating in competitive digital marketplaces (Saputra et al., 2023).

Recent advancements in deep learning, including the incorporation of attention mechanisms, have further enhanced the predictive capacity of time-series models. Although LSTM remains widely used, attention-based architectures such as Transformers have shown promise in modeling long-range dependencies and capturing complex interactions in sequential data (Sudirwo et al., 2023). Comparative studies indicate that while Transformers excel in large-scale datasets, LSTM often performs more efficiently in medium-sized datasets due to its simpler structure and lower computational cost. This makes LSTM a practical choice for merchants with substantial but not massive transaction histories, such as small online food stalls (Natzir et al., 2025).

Overall, existing literature demonstrates that deep learning, particularly LSTM, provides strong predictive performance in time-series analysis across multiple business domains. The ability of LSTM to model nonlinear patterns and long-term relationships makes it highly suitable for predicting sales transaction values in online food merchants. Such forecasting capabilities can significantly enhance operational planning, revenue management, and strategic business development. By applying LSTM to merchant-level transaction data, businesses can transform raw digital records into actionable insights that support sustainable growth and improved decision-making (Ren et al., 2023).

3. Research Methodology

Software tools used in this research include Google Colab as the primary cloud-based computational environment, supported by the Python programming language for model implementation. Data preprocessing and manipulation were carried out using Pandas and NumPy, while Scikit-Learn was utilized for scaling, dataset splitting, and model evaluation. The LSTM model was developed using TensorFlow and Keras, which provide high-level neural network APIs suitable for time-series forecasting. Visualization of trends and prediction performance was conducted using Matplotlib and Seaborn. Additionally, Google Drive integration was employed for dataset storage and experiment management. Hardware tools for this research using Nvidia RTX 4060 TI and i5-13600KF processor’s (Al-Husaini et al., 2024).

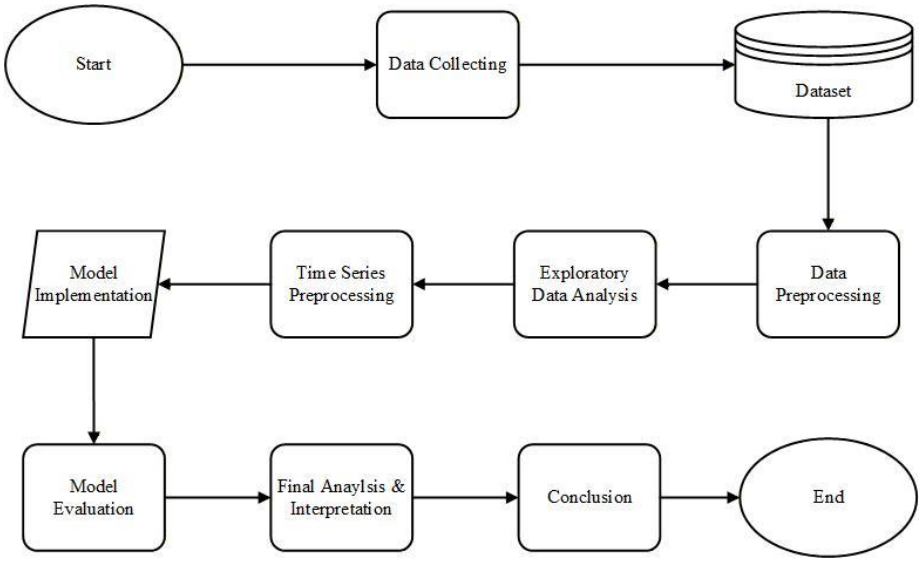

Figure. 1 : Method Flow

4. Results and Findings

The next step is dataset preparation, where the raw data is converted into a structured format suitable for time series modeling. This includes assigning a uniform daily time index, handling missing entries, and reformatting numerical values. Following this, data preprocessing is performed, consisting of cleaning incorrect values, removing anomalies, normalizing numeric features, and aggregating transaction values per day to ensure temporal uniformity. This stage ensures that the data is ready for analytical and predictive modeling.

An exploratory data analysis (EDA) is conducted to understand overall sales behavior, visualize historical trends, identify seasonality, and detect anomalies that may influence model performance. Techniques such as line charts, distribution plots, correlation analysis, and moving averages are used to reveal sales dynamics and customer demand patterns over time.

After EDA, a time series preprocessing phase is conducted to transform the dataset into a supervised learning structure. This includes generating input–output sequences using sliding windows, splitting data into training and testing sets, and applying normalization techniques such as Min–Max scaling to stabilize the learning process. The sequential nature of the data is preserved to ensure the LSTM model can effectively capture temporal dependencies.

Next, the model implementation stage involves developing and training the LSTM model using Python libraries such as TensorFlow, Keras, NumPy, and Pandas within the Google Colab computational environment. The LSTM architecture is designed to capture long-term sequential patterns, with parameters such as the number of neurons, batch size, number of epochs, and optimizer settings carefully configured based on preliminary experiments. The trained model is then used to generate predictions of future daily transaction values.

Once the model is trained, model evaluation is performed using established time series error metrics, specifically Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). These evaluation measures provide insight into the accuracy and reliability of the prediction model when compared to actual sales values. The evaluation results are analyzed to determine the model's strengths and limitations.

The final analysis and interpretation stage interprets the prediction results in the context of business insights for E-Stall Crunchy. This includes identifying potential periods of increased demand, understanding fluctuations, and proposing recommendations for inventory planning, promotional strategies, and operational optimization. The research ends with the conclusion, summarizing the findings and highlighting the effectiveness of LSTM for sales time series forecasting. It also outlines recommendations for future

improvements, such as incorporating external variables (weather, holidays, platform promotions) to enhance predictive performance.

Table 1 : Data Attribute Value Example

No	Date of Order	Value
1	2025-03-16	693.457
2	2025-03-17	877.173
3	2025-03-18	709.127
4	2025-03-19	438.804
5	2025-03-20	16.000

Dataset

Dataset used in this study was obtained from the daily sales transaction records of the online food merchant E-Stall Crunchy, which operates through digital food delivery platforms such as GoFood, GrabFood, ShopeeFood, and MaximFood. A total of 181 days of transaction data were collected, covering the period from September to March, representing real-world sales activities during operational hours of the merchant. Each data instance contains two primary attributes: date and transaction value, where the date represents the daily sales date and the transaction value represents the total amount of revenue (in Indonesian Rupiah) generated on that day.

The use of daily transaction value as the target variable serves an important purpose for both operational and strategic units of the business. For the operational side, such as production and inventory management, the data helps identify patterns in customer demand, peak ordering times, and supply requirements. For the managerial and marketing units, the monetary value of transactions provides insight into revenue trends, promotional effectiveness, seasonal fluctuations, and financial performance. This dual relevance makes the dataset suitable for time series forecasting using deep learning methods.

Prior to modeling, the dataset was examined for missing values, inconsistencies, and anomalies. The structure of the data ensures that each row represents one complete unit of daily transactional information. A concise summary of the attributes is presented in Table 1, describing the composition of the dataset used for the prediction of future transaction values at E-Stall Crunchy.

Data Prepocessing

Data preprocessing in this study was conducted to ensure that the raw sales data obtained from the e-stall Crunchy store could be reliably used for time series forecasting analysis. The cleaning procedure began by addressing missing values, particularly on dates where no transactions were recorded, which were treated as zero sales to maintain the continuity of the daily time index. Duplicate records were removed to avoid inflating sales values, and inconsistent data formats—such as variations in currency formatting or incorrect numerical types—were standardized into a unified structure. Outlier inspection was also performed to identify unusually high or low sales that might distort model training; outliers caused by data-entry anomalies were corrected or excluded, while natural fluctuations reflecting promotional events were preserved. Additionally, all date fields were converted into a consistent datetime format to comply with the requirements of time-series modeling. This preprocessing stage ensured that the dataset was clean, consistent, and structurally aligned before entering the exploratory analysis and time series–specific processing phase.

To ensure numerical stability and improve model convergence, all transaction values were normalized using the Min–Max Scaling technique. This approach transforms the original values into a fixed range of

[0,1], which is widely recommended for neural network–based time series models such as LSTM. The normalization process preserves the relative temporal patterns while reducing the impact of scale variations in the raw data. The scaling was implemented using the MinMaxScaler function from the Scikit-learn library, based on the following mathematical formulation :

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

where X represents the actual transaction value, while X_{min} and X_{max} denote the minimum and maximum values within the dataset. This preprocessing step ensures that the model receives data within a consistent range, thereby enhancing training efficiency and predictive performance.

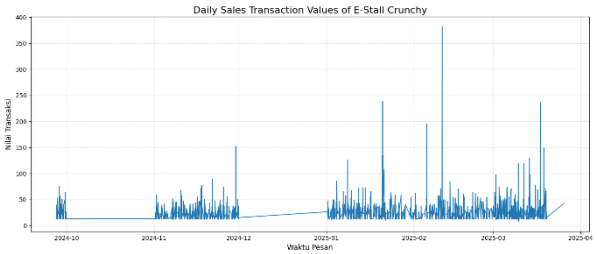

Figure 2 : Time Series Plot of Daily Sales Transactions

Exploratory Data Analysis

The time series visualization of the daily sales transaction values for E-Stall Crunchy shows a fluctuating pattern that reflects the dynamic nature of online food sales. As seen in Figure X, transaction values tend to vary significantly from day to day, with the majority of daily sales falling between IDR 15,000 and IDR 60,000. Several noticeable spikes appear throughout the observed period, with extreme peaks reaching above IDR 200,000 and even approaching IDR 380,000. These spikes likely represent days with unusually high order volumes, special events, promotions, or bulk purchases. Additionally, the plot reveals several periods of inactivity or near-zero values, which may correspond to days without transactions, interruptions in operations, or potential gaps in data recording. Toward the later months, the data exhibits a slight upward trend in both baseline and peak transaction values, indicating potential growth in customer demand. This exploratory visualization is essential for identifying patterns, seasonality, and anomalies, which later guide the model selection and preprocessing strategies for LSTM-based forecasting.

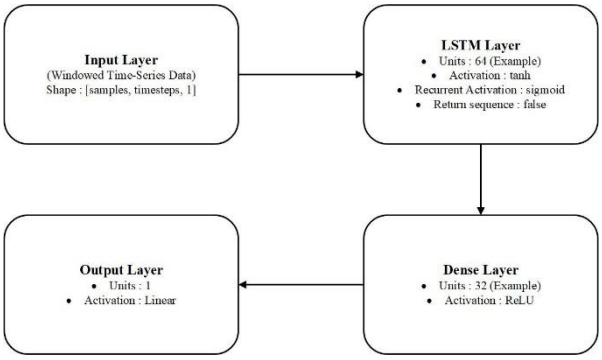

Figure 3 : LSTM Architechture

Model Implementation

The LSTM model architecture used in this study consists of four main components: an input layer, an LSTM layer, a dense layer, and a final output layer. The input layer receives the windowed time-series data that has been transformed into the shape of [samples, timesteps, features], where the feature dimension corresponds to the normalized sales value. The core of the architecture is a single LSTM layer, configured with a specific

number of hidden units—commonly 64 in this study—which enables the model to capture long-term patterns and temporal dependencies present in the sales history. The LSTM layer uses the tanh activation function for its cell states and sigmoid for its gating mechanisms. Following the LSTM layer, a fully connected dense layer with ReLU activation is applied to refine the learned representations and enhance non-linear modeling capability. Finally, a single-unit output layer with a linear activation function is used to generate the final predicted sales value. This architecture is optimized using the Adam optimizer and trained using the Mean Squared Error (MSE) loss function.

Result and Discussion

The experimental phase of this study was carried out by defining several key parameters used in the LSTM model, namely the number of epochs, the look-back window size, and the training–testing data split ratio. These parameters were varied to determine the configuration that produces the highest predictive accuracy for the sales transaction time series.

Table 2 : Parameter Testing and Training

Parameter	1	2	3
Dataset (D)	70/30	80/20	90/10
Range (R)	[0,1]	[-1,1]	
Look Back (L)	1	2	3

The experiment used three parameter configurations consisting of different dataset split ratios, normalization ranges, and look-back values. The dataset split determines how the data is divided into training and testing sets, while the normalization range [0,1] or [-1,1] ensures the input values are scaled appropriately for the LSTM model. The look-back parameter specifies how many previous time steps are used to predict the next value. The complete parameter settings used in the testing and training process are summarized in Table 2.

Table 3 : Experimental Scenario

Scenario	Information
1	D1, R1, L1
2	D1, R1, L2
3	D1, R1, L3
4	D1, R2, L1
5	D1, R2, L2
6	D1, R2, L3
7	D2, R1, L1
8	D2, R1, L2
9	D2, R1, L3
10	D2, R2, L1
11	D2, R2, L2
12	D2, R2, L3
13	D3, R1, L1
14	D3, R1, L2
15	D3, R1, L3
16	D3, R2, L1
17	D3, R2, L2
18	D3, R2, L3

To evaluate the model performance under various conditions, eighteen experimental scenarios were constructed by combining different dataset splits (D), normalization ranges (R), and look-back values (L). Each scenario represents a unique configuration based on the parameters defined earlier. These

combinations were systematically arranged to ensure that the LSTM model was tested across all possible parameter variations. This approach allows the study to identify which configuration yields the most accurate prediction of sales transaction values. The complete list of experimental scenarios is presented in Table 3.

Table 4 : RMSE and MAPE Result

No	Scenario	RMSE Train	RMSE Test	MAPE Train	MAPE Test
1	D1, R1, L1	164826.87	133556.3	1021.33	1062.91
2	D1, R1, L2	164066.92	132538.85	840.0	869.62
3	D1, R1, L3	163950.77	132559.22	956.97	991.06
4	D1, R2, L1	165933.18	135051.24	656.44	687.44
5	D1, R2, L2	164331.98	132902.91	780.71	807.76
6	D1, R2, L3	164189.41	132384.45	944.81	980.31
7	D2, R1, L1	161005.44	132366.6	883.58	1105.46
8	D2, R1, L2	160721.97	132759.32	929.94	1157.82
9	D2, R1, L3	160566.24	132443.47	813.77	1005.83
10	D2, R2, L1	161257.6	132338.77	782.11	980.56
11	D2, R2, L2	160735.24	132414.25	813.43	1010.76
12	D2, R2, L3	168651.35	143140.78	1382.57	1705.25
13	D3, R1, L1	156553.52	147751.38	921.76	715.65
14	D3, R1, L2	156210.47	147373.63	949.83	748.16
15	D3, R1, L3	156023.81	147868.02	894.29	709.11
16	D3, R2, L1	157034.53	149621.64	778.66	606.0
17	D3, R2, L2	157606.13	147244.53	1137.94	892.85
18	D3, R2, L3	157982.2	146826.96	1148.89	903.26

Based on the results presented in Table 4, the performance of the LSTM model varies across scenarios, influenced by differences in dataset split (D1–D3), normalization range (R1–R2), and look-back values (L1–L3). Overall, scenarios using a larger training portion, particularly D3 with a 90%–10% train–test split, consistently produce lower RMSE and MAPE values, indicating better generalization and learning stability. This suggests that the model benefits substantially from having more historical data available during training. In terms of normalization, scenarios using the range [−1,1] (R2) tend to outperform those using [0,1], which aligns with the characteristics of LSTM activation functions that operate more effectively when inputs are centered around zero. The look-back parameter also affects performance, with look-back values of 2 and 3 (L2 and L3) generally yielding improved prediction accuracy compared to L1, as they provide the model with richer temporal context. Among all configurations, scenarios combining D3 with L3—specifically Scenario 15 and Scenario 18—demonstrate the best overall performance, achieving the lowest RMSE and relatively lower MAPE on the testing dataset.

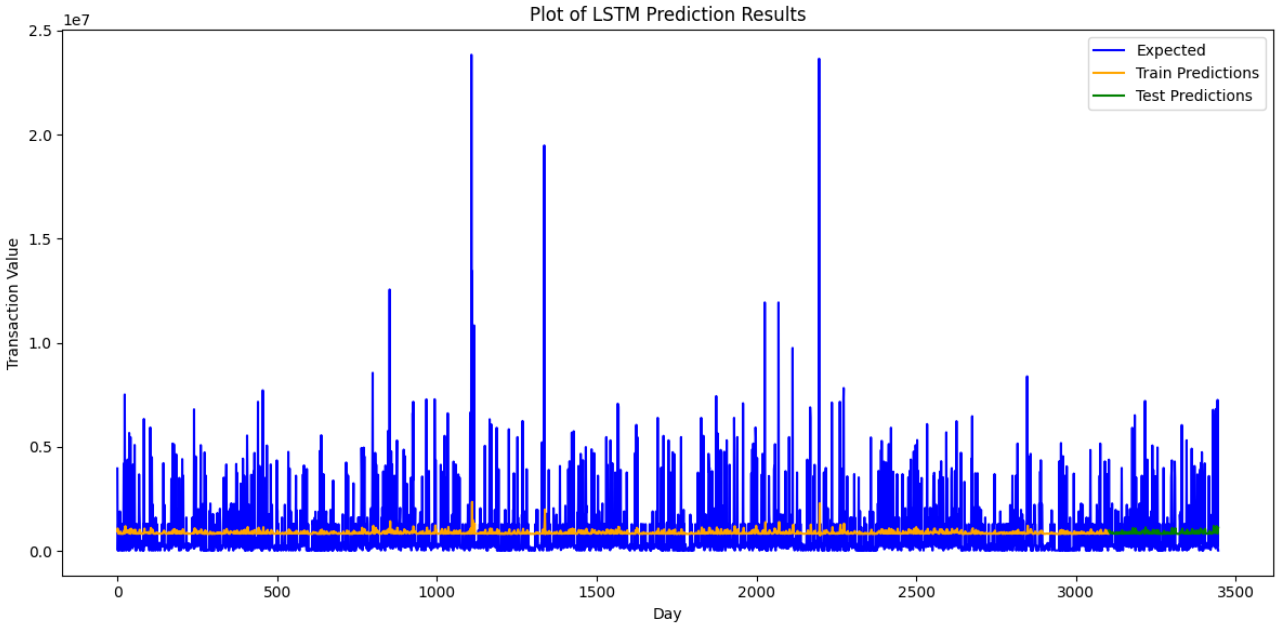

Figure 4 : RMSE and MAPE Result

The visualization in Figure 4 illustrates the comparison between the actual transaction values and the predictions generated by the LSTM model for both the training and testing datasets. As shown in the plot, the actual transaction values exhibit extremely high variance with frequent and sharp spikes, reflecting the naturally irregular and volatile behavior of transaction amounts in the dataset. In contrast, both the training and testing prediction curves appear significantly smoother and remain at a much lower amplitude compared to the true values. This indicates that the LSTM model was able to capture the general trend but struggled to learn and reproduce the extreme fluctuations present in the data. Such behavior is expected when the dataset contains abrupt spikes, outliers, or highly inconsistent patterns that are difficult for sequence-based models to learn without additional feature inputs.

The gap between the expected values and the predicted lines suggests that the model was not able to accurately track the magnitude of sudden transaction changes, resulting in underestimation during peak periods and over-smoothing across the sequence. This is consistent with the high RMSE and MAPE values observed during evaluation. The model tends to predict values closer to the mean behavior of the training data rather than responding dynamically to abrupt changes. Despite this limitation, the prediction pattern remains stable across both training and testing phases, which indicates that the model did not experience severe overfitting. Overall, the plot demonstrates that the LSTM model can approximate the general pattern of the time series but has difficulty modeling large and sudden fluctuations in transaction values, suggesting that further improvements may require additional features, outlier handling, or more advanced architectures

5. Conclusion

This study evaluated the use of the Long Short-Term Memory (LSTM) model to predict time series sales transaction values of e-stall merchants. Based on a comprehensive set of eighteen experimental scenarios combining different data split ratios, normalization ranges, and look-back windows, the results indicate that the LSTM model is capable of learning general temporal patterns but struggles to accurately model the highly volatile and irregular nature of the transaction data. Scenarios using a larger training proportion (D3 with a 90/10 split) consistently produced lower RMSE and MAPE values, suggesting that additional training data improves the model's ability to capture underlying trends. Similarly, normalization within the range of $[-1,1]$ and longer look-back windows (L3) contributed to improved prediction performance, as they provide better numerical stability and richer temporal context.

Despite these optimizations, the prediction outputs remained significantly smoother than the actual

transaction values, as visualized in the prediction plot. The presence of extreme spikes and abrupt value changes in the dataset posed challenges for the LSTM model, resulting in consistent underestimation of peak values and high error metrics. This indicates that although the LSTM architecture can approximate overall movement in the data, it is not fully effective in modeling datasets with high variance and irregular fluctuations when used with a single-variable input.

Overall, the findings suggest that LSTM provides a reasonable baseline for trend learning but is limited in precision for highly volatile sales transaction forecasting. Future improvements may include incorporating additional features (such as day-of-week, promotions, discounts, and external factors), applying outlier handling techniques, or exploring more advanced architectures such as stacked LSTM, GRU, or attention-based models to better capture complex patterns in merchant transaction behavior.

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