

Sales Forecasting Model for Indonesian Clothing MSMEs For Sales Strategy Optimization Using The Long Short-Term Memory Method

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Abstract

Micro, Small, and Medium Enterprises (MSMEs) in the clothing industry are one of the key pillars of the economy, contributing significantly to Gross Domestic Product (GDP) and employment. However, MSMEs face considerable challenges related to market competition, shifting consumer trends, and fluctuating demand. Advances in data analytics and machine learning offer solutions to improve sales forecasting accuracy, thereby supporting more effective business strategies. This study aims to develop a sales forecasting model based on Long Short-Term Memory (LSTM) tailored to the characteristics of clothing MSMEs in Indonesia. The research was conducted at Ananda Kids MSME in Purbalingga, using 30,885 daily transaction records collected over 23 months. The dataset included product categories, sales volume, and revenue, which were further processed through normalization, handling of missing values, and the addition of seasonal features. The LSTM model was designed with 128 neurons and evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The findings indicate that the LSTM model achieved high accuracy for certain product categories. The “Set” and “Children’s Fashion” categories recorded MAPE values below 10%, demonstrating the model’s effectiveness in forecasting stable sales patterns. In contrast, categories with high volatility, such as accessories, produced larger prediction errors. These results highlight that data quality and sales pattern stability are crucial factors in enhancing model performance. Overall, the study demonstrates that the application of LSTM holds significant potential in supporting strategic decision-making for MSMEs through more accurate sales forecasting. Beyond its practical contributions for business actors, the study also provides a basis for the development of digitalization policies for the MSME sector in Indonesia.

Keywords : *Clothing Industry, LSTM, Machine Learning, MSMEs, Sales Forecasting*

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1. INTRODUCTION

Micro, Small, and Medium Enterprises (MSMEs) in the clothing industry are a key pillar of the economy, both in Indonesia and in many other countries [1]. This sector contributes significantly to Gross Domestic Product (GDP) and absorbs a large workforce [2]. However, MSMEs in the clothing industry face various challenges in the face of increasingly fierce market competition, changing consumer trends, and unpredictable demand fluctuations [3]. Therefore, a data-driven sales strategy is needed to optimize revenue and business competitiveness.

Along with the development of artificial intelligence and data analysis technology, machine learning-based predictive approaches are increasingly used in the retail and MSME sectors [4]. In terms of time series data analysis, traditional time series prediction models, such as ARIMA and Vector Autoregression (VAR) models, have several weaknesses due to the nonlinear and heterogeneous nature of sales data [5]. On the other hand, deep learning algorithms have made significant progress [6]. In

recent years, the application of machine learning in time series prediction has become increasingly important and has generally outperformed the prediction accuracy of classical time series models [7]. One method that has proven to be more effective in time series data analysis is Long Short-Term Memory (LSTM), a deep neural network architecture designed to handle data with long-term dependencies [8], [9]. Various studies, including in finance and hydrology, have shown that LSTM excels at predicting nonlinear and inhomogeneous time series [10], [11], [12], [13], [14]. Furthermore, several previous studies have widely used LSTM to forecast sales and optimize marketing strategies in various industrial sectors, including e-commerce [15], conventional retail [16], and the food and beverage sector [17].

Several studies have explored the use of LSTM in the clothing industry. For example, studies conducted by [18], [19] showed that applying LSTM to clothing retail sales prediction can improve prediction accuracy by up to 15% compared to traditional regression methods. Furthermore, research by [20] proposed a hybrid model that combines LSTM with a stock optimization algorithm, which significantly reduces the risk of overstocking or understocking in the fashion retail sector.

However, research related to the application of LSTM in the clothing industry for MSMEs is still very limited, especially in the Indonesian context. Studies by [21], [22] only highlight the use of simple transaction data without considering external factors such as market trends, weather, or promotional campaigns. Furthermore, other studies by [23], [24] indicate that many MSMEs still have not optimally utilized data analysis in strategic decision-making. One of the main challenges faced by MSMEs is the lack of utilization of customer data to support strategic decision-making. Yet, in the current digital era, data has become a crucial asset that can provide valuable insights in understanding customer preferences, identifying market trends, and designing effective business strategies [25], [26], [27]. Sales data such as the number of visitors, conversion rates, and average sales are often not optimally utilized, so the potential for increased sales and operational efficiency cannot be maximized.

This study aims to fill this gap in the literature by developing an LSTM-based sales prediction model tailored for MSMEs in the clothing industry in Indonesia. By utilizing various data sources, such as historical transaction data, social media, and other external factors, this research is expected to significantly contribute to helping MSMEs optimize their sales strategies. The results will not only provide insights for business owners but also inform the development of policies supporting MSME digitalization in the data-driven economy.

In addition, this study introduces a methodological contribution by developing a multivariate LSTM model that incorporates several domain-specific preprocessing techniques, including log transformation, MinMax normalization, missing-value handling, and seasonal feature engineering using cyclical encodings (month_sin and month_cos). A 12-month sliding window is used to capture long-term temporal dependencies, and the model simultaneously predicts two output variables, sales volume and revenue, based on historical patterns. This novelty strengthens the model's applicability to MSME-scale datasets, which often exhibit volatility and irregular patterns. The proposed approach provides contributions both methodologically and practically, offering actionable insights for MSMEs and supporting the development of data-driven digitalization policies in Indonesia.

Based on Figure 1, this study employed a quantitative method with a multivariate data-driven analytical approach derived from a dataset of MSMEs in the clothing industry. A Long Short-Term Memory (LSTM)-based prediction model was chosen for its superior ability to capture temporal patterns in time-series data. This research method was systematically designed to achieve comprehensive results, including research procedures, expected outcomes, and targeted achievement indicators.

2. METHOD

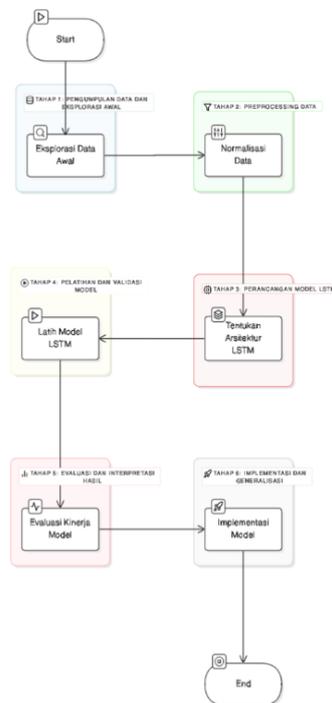


Figure 1. Research Method

This research was conducted through six main stages

1. Data Collection and Initial Exploration
 - a. The dataset was collected from MSMEs in the clothing industry, including:
 - Visitor data.
 - Conversion rate data.
 - Daily/monthly sales data.
 - Average sales data.
 - b. Initial exploration was conducted to understand seasonal patterns, anomalies, and relationships between variables.
2. Preprocessing Data
 - a. Handle missing values using interpolation or imputation.
 - b. Normalize the data to stay within a certain range to improve the stability of the LSTM model.
 - c. Transform the data if necessary to address skewness or outliers.
 - d. To align with the actual experimental setup, preprocessing included:
 - log transformation (log1p) for Total Amount and Revenue,
 - MinMaxScaler normalization,
 - creation of Month, Year, Quarter variables,
 - cyclical encoding using month_sin and month_cos,
 - creation of a Lebaran indicator variable,
 - removal of incomplete data (December 2024),
 - aggregation into monthly-level timeseries.
3. LSTM Model Design
 - a. Number of layers.
 - b. The input and output dimensions correspond to multivariate data.

- c. The model was implemented as a multivariate–multioutput LSTM with the following architecture:
 - LSTM layer with 128 units,
 - dropout 20%,
 - Dense-ReLU layer (intermediate),
 - Dense output layer with two neurons for dual prediction (Total Amount & Revenue).
 - Adam optimizer with learning rate 5×10^{-4} and MAE loss function.
- 4. Model Training and Validation
 - a. The model is trained using the training set.
 - b. Model performance is evaluated on the validation set to avoid overfitting.
 - c. Training used an 80:20 split with a 12-month sliding window to capture long-term seasonal patterns.
 - d. EarlyStopping and ModelCheckpoint callbacks were applied to prevent overfitting, and convergence typically occurred between epochs 40–90.
- 5. Evaluation and Interpretation of Results
 - a. The model was tested using a test set.
 - b. Predicted results were compared with actual data to validate the model's accuracy.
 - c. Sensitivity analysis was performed to understand the contribution of each variable in the model.
 - d. Evaluation used multiple performance metrics (MAE, RMSE, MAPE) consistent with time-series forecasting standards. The mathematical formulations for these metrics are defined as follows:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (2)$$

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

- e. Interpretation focused on assessing seasonal learnability, stability across product categories, and the model's ability to generalize within the same MSME dataset.
- 6. Implementation and Generalization
 - a. The validated model was applied to MSME data for sales prediction.
 - b. The prediction results were used to provide strategic recommendations to MSMEs.
 - c. The model's generalizability was tested with datasets from other MSMEs to assess its robustness.
 - d. In this study, implementation was carried out in the form of three-month ahead predictions for each product category using an autoregressive forecasting procedure.
 - e. Generalization to other MSMEs was conceptually discussed, but not empirically executed, as the available dataset only came from one MSME source.

3. RESULT

This chapter presents the results of implementing a Long Short-Term Memory (LSTM) model to analyze and predict monthly sales data for MSMEs in the clothing industry. The discussion begins with a description of the dataset used, followed by data preprocessing steps, model architecture, performance evaluation results, and an in-depth analysis of the resulting predictions.

3.1. Data Collection and Initial Exploration

Table 1. UMKM Clothing Sales Datas

Timestamp	Category	Amount	Price	...
2023-01-02 08:42:05	Muslim Fashion	1.0	47000.0	...
2023-01-02 08:42:49	Baby and Kids Fashion	1.0	125000.0	...
2023-01-02 08:44:42	Baby and Kids Fashion	2.0	125000.0	...
2023-01-02 08:47:26	Set	1.0	45000.0	...
...

Table 1 presents sample Point of Sales (POS) data from a clothing industry MSME used in this study. The raw data includes 30,885 daily transactions over 23 months, from January 1, 2023, to November 30, 2024. Each row in the raw data represents a single transaction.

Initial exploratory analysis was also conducted to understand the overall structure and characteristics of the dataset before entering the preprocessing stage. The exploratory results showed that a total of 30,885 transaction records were distributed across seven major product categories, with the largest transaction frequencies found in Baby & Kids Fashion (11,833 transactions), Sets (6,207), and Muslim Fashion (4,741). Meanwhile, certain categories such as Men’s Clothing contained very limited data (only 38 records), indicating potential issues for time-series modeling due to insufficient historical coverage.

This study focuses on four main features: a timestamp that records the date and time of each sales transaction; a category that represents the type of product sold; the number of product units sold; and the selling price per unit. In addition to these four main features, the dataset also contains other columns such as transaction code, cashier, and payment method. However, these features were not used in the study as they were not relevant to the purpose of forecasting sales time series. All recorded product categories are grouped into seven main categories: Other Baby & Kids Fashion, Sets, Muslim Fashion, Women’s Clothing, Accessories and Other Items, Series Clothing, and Men’s Clothing.

3.2. Preprocessing Data

This research focuses on four key features: a timestamp that records the date and time of each sales transaction, a category that represents the type of product sold, and the number of product units. These raw variables were later transformed into aggregated and derived temporal features, as detailed in Table 2 and Table 3.

The Revenue column is created by multiplying the Amount column by the Selling Price to obtain the gross revenue before discounts. To allow for data aggregation, a Month column is also created by extracting the year and month information from the original Timestamp column. The data is then aggregated by category and month by summing Total_Amount and Revenue. The aggregation results can be seen in Table 2.

In addition to the monthly aggregation, several temporal and contextual features were added to strengthen the model’s ability to capture seasonal and cyclical patterns. These include the year, month number, quarter, and Eid marker. Table 3 below shows a sample of the dataset after these features were successfully added.

Table 2. Monthly Aggregation Results

Category	Month	Total Amount	Revenue
Accessories and Other Items Category	2023-01-01	183.0	13355000.0
Accessories and Other Items Category	2023-02-01	69.0	4515000.0
...
Set	2024-07-01	390.0	41854500.0
Set	2024-08-01	341.0	38483500.0

Table 3. Added Time-Based and Contextual Features

Category	Month	Total Amount	Revenue	Year	Month Number	Quartal	Eid Marker	Month Sin	Month Cos
Accessories and Other Items Category	2023-01-01	183.0	13355000.0	2023	1	1	0	0.5	0.866025
Set	2023-01-01	285.0	27912000.0	2023	1	1	0	0.5	0.866025
Clothing Series Women's Clothing	2023-01-01	56.0	5404000.0	2023	1	1	0	0.5	0.866025
...

These engineered features strengthen the model’s ability to capture seasonal behaviors, quarterly demand patterns, and sales spikes associated with events such as Ramadan and Eid al-Fitr. In addition, to properly represent the cyclical nature of monthly seasonality, the Month variable was also transformed using sine and cosine encoding (month_sin and month_cos). This transformation ensures that the model recognizes December and January as adjacent periods, avoiding artificial discontinuities commonly introduced by integer month encoding. Cyclical encoding using sin–cos functions has been widely adopted in recent time-series forecasting research because it preserves rotational continuity and enhances the learning stability of neural networks when modeling repeating seasonal patterns [28], [29]. This process can be seen in Figures 2 and 3.

```

monthly_cat['Tahun'] = monthly_cat['Bulan'].dt.year
monthly_cat['Nomor_Bulan'] = monthly_cat['Bulan'].dt.month
monthly_cat['Kuartal'] = monthly_cat['Bulan'].dt.quarter

# Membuat penanda Lebaran (biasanya penjualan meningkat di bulan Ramadhan dan Idul Fitri)
# Idul Fitri 2023: April, Ramadhan dimulai Maret.
# Idul Fitri 2024: April, Ramadhan dimulai Maret.
lebaran_months_2023 = [3, 4]
lebaran_months_2024 = [3, 4]

monthly_cat['Penanda_Lebaran'] = 0
monthly_cat.loc[(monthly_cat['Tahun'] == 2023) & (monthly_cat['Nomor_Bulan'].isin(lebaran_months_2023)), 'Penanda_Lebaran'] = 1
monthly_cat.loc[(monthly_cat['Tahun'] == 2024) & (monthly_cat['Nomor_Bulan'].isin(lebaran_months_2024)), 'Penanda_Lebaran'] = 1
    
```

Figure 2. Added time feature

```
# Fitur tambahan: musiman
data_kat['month'] = data_kat['Bulan'].dt.month
data_kat['month_sin'] = np.sin(2 * np.pi * data_kat['month'] / 12)
data_kat['month_cos'] = np.cos(2 * np.pi * data_kat['month'] / 12)
```

Figure 3. Addition of seasonal features

The next step is to handle incomplete data. Data for December 2024 was removed because it only covers the first few days and could potentially mislead the model. The model may assume this is due to a drastic drop in sales. This process can be seen in Figure 4.

```
# Hapus Bulan Desember 2024
monthly_cat = monthly_cat[monthly_cat['Bulan'] != '2024-12-01']
```

Figure 4. Incomplete data handling

Finally, a logarithmic transformation (\log_{1p}) was performed on Total Amount and Revenue to stabilize the variance, followed by MinMax normalization to the $[0,1]$ range to suit the needs of the LSTM model. This process can be seen in Figure 5.

```
# Log transform
data_kat['Total_Jumlah_Log'] = np.log1p(data_kat['Total_Jumlah'])
data_kat['Pendapatan_Log'] = np.log1p(data_kat['Pendapatan'])

# Scaling
scaler_jumlah = MinMaxScaler()
scaler_pendapatan = MinMaxScaler()
scaler_month = MinMaxScaler()

jumlah_scaled = scaler_jumlah.fit_transform(data_kat[['Total_Jumlah_Log']])
pendapatan_scaled = scaler_pendapatan.fit_transform(data_kat[['Pendapatan_Log']])
sin_cos_scaled = scaler_month.fit_transform(data_kat[['month_sin', 'month_cos']])

scaled_data = np.hstack((jumlah_scaled, pendapatan_scaled, sin_cos_scaled))
```

Figure 5. Data transformation and scaling

3.3. LSTM Model Design

This study implements a Long Short-Term Memory (LSTM) model for monthly sales forecasting per product category. To ensure reproducibility, the experimental framework was implemented using the Python programming language. Data manipulation and analysis were performed using Pandas and NumPy, while Matplotlib and Seaborn were utilized for data visualization. The LSTM model architecture was constructed using the TensorFlow framework with the Keras API, and Scikit-learn was employed for data normalization and performance evaluation metrics. In Table 4, the Window Size is set to 12, representing the use of 12 months of historical data as input features. The model architecture consists of one LSTM layer with 128 units, followed by a Dropout layer (20%) for regularization, and a Dense hidden layer with 25 units.

During the training process, the model was optimized using Adam with a learning rate of 0.0005 and a Mean Absolute Error (MAE) loss function. Training was run with a batch size of 16 for a maximum of 200 epochs, with an EarlyStopping mechanism that would stop the process if there was no improvement in the validation data after 15 epochs.

Table 4. LSTM Model Hyperparameters

Hyperparameter	Value	Description
Window Size	12	The length of the historical sequence (12 months) used as input features.
Input Shape	(12, 4)	The input sequence has 12 timesteps and 4 features (Log_Amount, Log_Income, month_sin, month_cos) per timestep.
Arsitektur Lapisan	LSTM -> Dropout -> Dense -> Dense	The flow of layers in the sequential model.
Unit LSTM	128	The number of neurons in the LSTM layer to capture temporal dependencies.
Unit Dense	25 (Hidden), 2 (Output)	25 neurons in the hidden layer and 2 neurons in the output layer for Amount & Revenue prediction.
Dropout Rate	0.2	The percentage of neurons (20%) that are randomly deactivated during training for regularization.
Optimizer	Adam	The adaptive optimization algorithm used.
Learning Rate	0.0005 (5e-4)	The learning rate used by the Adam optimizer.
Loss Function	Mean Absolute Error (MAE)	The metric is minimized during training, which is more robust against outliers.
Batch Size	16	The number of data samples processed in one iteration.
Epochs	Maximal 200	The maximum number of training rounds stopped early by EarlyStopping.
Patience	15	The number of epochs to wait for improvement before EarlyStopping stops training.
Activation Function	Tanh (LSTM), ReLU (Dense), Linear (Output)	The activation function used in each layer.

3.4. Results of Model Training and Validation

This subsection reports the training and validation behavior of the LSTM model for all product categories included in the analysis. The learning curves for each category are presented in Figure 6.



Figure 6. Validation Loss Across All Categories

The model was trained for a maximum of 200 epochs, but the validation loss across all categories consistently showed a clear convergence pattern within the first 30–50 epochs, after which further improvements became minimal. This indicates that the model had reached a stable learning state well before the maximum epoch limit.

While most categories stabilized smoothly, some volatility was observed in the early-to-mid training phases (epochs 10–25), particularly in the Fashion Muslim category. The Aksesoris category also displayed mild fluctuations in later epochs. These behaviors likely reflect higher variance or limited historical data in these specific segments. Notably, the validation loss remained consistently lower than or close to the training loss. This behavior is attributed to the 20% dropout layer, which introduces noise during the training phase but is deactivated during validation. Consequently, no signs of overfitting were observed, confirming that the applied regularization strategies, dropout (20%), MAE loss, and Adam optimizer with a 5×10^{-4} learning rate, were effective in preventing overfitting.

Across categories, the validation curves also reflected the differing complexity of each product type. Categories with more stable and higher-frequency sales signals (e.g., Set, Pakaian Perempuan) demonstrated a smoother decrease in validation loss, while categories with more irregular patterns showed slightly noisier convergence. Overall, the learning dynamics indicate that the model was able to generalize adequately to unseen segments of the time series.

3.5. Evaluation and Interpretation of Results

The LSTM model, whose architecture was detailed in the previous chapter, was evaluated on validation data. Model performance was measured using the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) metrics to provide a comprehensive performance overview. The quantitative evaluation results for each product category are presented in Table 5.

Table 5. LSTM Model Evaluation

Category	Matrix	MAE	RMSE	MAPE (%)
Accessories and Other Items Category	Amount	45.60	46.45	24.66
	Revenue	3,114,747.33	4,554,648.15	29.99
Set	Amount	13.27	18.45	4.43
	Revenue	2,907,504.00	4,151,417.20	9.25
Clothing Series	Amount	9.01	9.05	26.10
	Revenue	680,378.17	685,636.95	21.20
Women's Clothing	Amount	34.05	37.49	18.99
	Revenue	2,694,511.00	3,284,856.06	21.03
Muslim Fashion	Amount	19.33	30.41	19.49
	Revenue	2,281,232.67	2,801,983.24	25.13
Baby and Kids Fashion	Amount	45.72	54.56	8.19
	Revenue	1,033,152.00	1,294,699.79	2.51

The Men's Clothing category could not be evaluated because the amount of monthly historical data for that category did not meet the minimum requirement of 17 months of data, based on a window size of 12.

Based on the Mean Absolute Percentage Error (MAPE) metric, the LSTM model demonstrated excellent performance in categories with relatively stable sales patterns and high transaction volumes. The Sets and Other Baby & Kids Fashion categories recorded error rates below 10%, which can be categorized as high-accuracy forecasting. The Women's Clothing and Muslim Fashion categories also performed satisfactorily with MAPEs below 25%, indicating that the model's predictions for these categories were, on average, close to the actual data. This interpretation aligns with Lewis's scale of accuracy, which classifies a MAPE of less than 10% as highly accurate forecasting, 10% to 20% as good forecasting, and 20% to 50% as reasonable forecasting [30]. From an accuracy perspective, these findings confirm the LSTM's success in modeling sales patterns in product segments with stable characteristics.

Conversely, the suboptimal performance in categories like Accessories and Series Clothing indicates that the relatively short historical data coverage of approximately 23 months is a major limitation of this study. Even with LSTM architectures capable of capturing long-term dependencies, limited data volumes and incomplete seasonal cycles remain obstacles for the model in consistently generalizing patterns across categories.

3.6. Implementation and Generalization

Table 6. LSTM Forecasting Results

Category	Month Prediction	Amount (unit)	Revenue (Rp)
Accessories and Other Items Category	1st Month	206.23	14,553,184.00
	2nd Month	215.48	14,509,919.00
	3rd Month	229.63	15,174,625.00
Set	1st Month	275.69	36,322,832.00
	2nd Month	277.20	36,420,716.00
	3rd Month	279.24	36,793,636.00
Clothing Series	1st Month	39.57	3,757,257.75
	2nd Month	41.04	3,611,710.50
	3rd Month	43.93	3,522,229.50
Women's Clothing	1st Month	193.50	13,917,717.00
	2nd Month	203.15	14,582,137.00
	3rd Month	212.93	15,286,001.00
Muslim Fashion	1st Month	54.62	6,553,512.00
	2nd Month	55.46	6,293,141.50
	3rd Month	56.22	6,177,245.00
Baby and Kids Fashion	1st Month	485.57	41,442,196.00
	2nd Month	489.69	41,241,280.00
	3rd Month	495.54	41,689,232.00

Using historical data up to the most recent month available (November 2024), the trained LSTM model is used to recursively predict total sales and revenue for the next three months. The forecasting results for each category are presented in Table 6.

To gain a deeper understanding of the model's behaviour for each product segment, individual visual analysis was performed. The following graph compares actual historical data (black line), predicted results based on validation data (dotted line), and the forecast for the next three months (dotted line with markers). Across all product categories, the predicted validation curves appear noticeably smoother than the actual historical data. This occurs because the LSTM model captures the dominant long-term temporal structure while filtering out short-term fluctuations and irregularities. Since the model is trained on limited monthly observations, it naturally prioritizes stable trend components rather than high-frequency noise. This smoothing effect is a common characteristic of deep learning models used for time-series forecasting, especially when applying sliding-window training on multivariate monthly data.

1. Accessories and Other Items Category

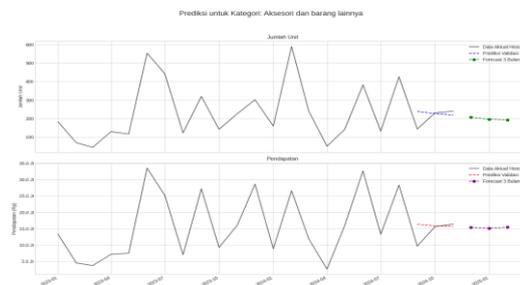


Figure 7. Visualization of Accessories and Other Items Category Predictions

As seen in Figure 7, this category shows adequate performance with MAPEs in the 24-30% range. Visually, this is a good example of a model that successfully learns the mean or baseline value of the data, but fails completely to capture the peaks and valleys. The prediction line appears relatively flat compared to the highly volatile actual data, indicating that the signal in this data is weaker and more difficult to learn.

2. Category Set

As seen in Figure 8, the Set model demonstrates very high accuracy performance, as confirmed by the MAPE values for Amount (4.43%) and Revenue (9.25%). The visualization shows that the prediction lines (blue and red) follow the general trend of the actual data quite well.

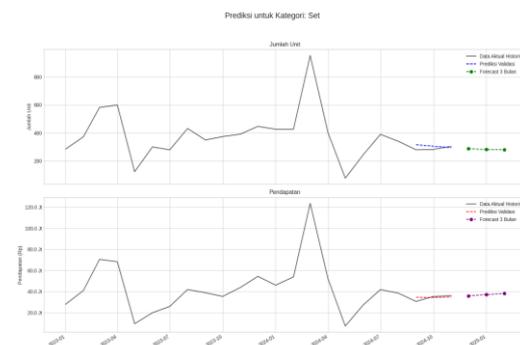
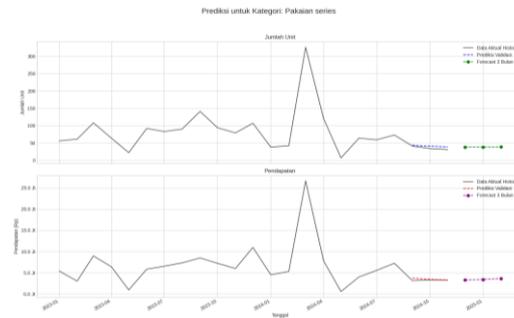


Figure 8. Visualization of Prediction Category Set

3. Clothing Series Category



Gambar 9. Visualization of Clothing Category Prediction Series

Figure 9 shows that the model consistently follows the historical trend, including a decline after the peak in early 2024. During the validation phase, the predicted line closely adhered to the actual pattern, indicating the model's ability to capture monthly sales dynamics well. The subsequent three-month projections show trends consistent with previous seasonal patterns, providing a realistic picture of potential future sales volume and revenue.

4. Women's Clothing Category

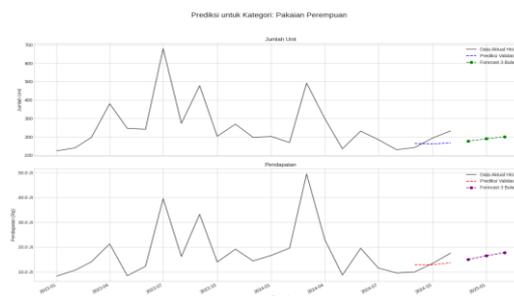


Figure 10. Visualization of Women's Clothing Category Predictions

As shown in Figure 10, the model performs reasonably well for the Women's Apparel category, with a MAPE value of around 19-21%. The graph shows that the model's predictions successfully capture the general up-and-down pattern of historical data. However, it's clear that the volatility, or swings, of the predicted line are much smaller than those of the actual data. The model successfully learns the underlying trend but is unable to replicate the volatility characteristic of this product's sales.

5. Muslim Fashion Category

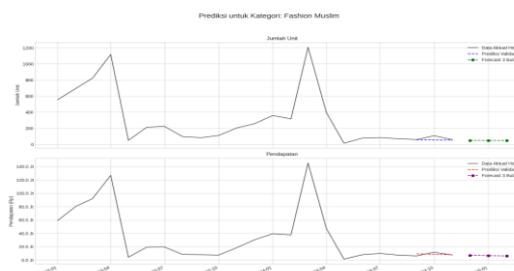


Figure 11. Visualization of Muslim Fashion Category Predictions

The visualization in Figure 11 shows that the model's performance in this category can be classified as good, with a MAPE in the 19-25% range. The visualization demonstrates that the model is able to follow the direction of the data movement. However, there are several points where the predictions are significantly off, particularly when trying to predict peak sales around the Eid al-Fitr period, demonstrating the model's difficulty in generalizing seasonal events that are not always identical each year.

6. Other Baby and Kids Fashion Categories

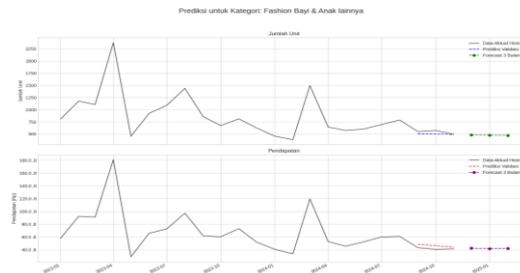


Figure 12. Visualization of Baby and Other Children's Fashion Category Predictions

Figure 12 shows that this category performed the best of all categories, particularly in the Revenue metric, with a MAPE of only 2.51%. Visually, the prediction line closely follows the actual data pattern.

4. DISCUSSION

The results of this study confirm that the implemented Long Short-Term Memory (LSTM) model is capable of producing forecasts with a high degree of accuracy across several product categories. This finding aligns with various previous studies highlighting the superiority of LSTM in predicting complex time series [15], [16], [17]. Specifically, the model's success in achieving Mean Absolute Percentage Error (MAPE) values below 10% in the "Set" and "Other Baby & Kids Fashion" categories confirms LSTM's potential as a reliable forecasting tool in the retail sector.

This success can be attributed to the effectiveness of the data pre-processing stage, particularly the application of cyclical seasonal features (month_sin and month_cos). These results reinforce the argument that although LSTM is theoretically capable of capturing long-term dependencies [10], [11], its performance can be significantly improved through appropriate feature engineering, particularly when historical data has a relatively limited time span.

To provide a clearer context regarding the position of this research among existing literature, Table 7 presents a comparative analysis between the proposed model and several related studies in the fashion and retail forecasting domain.

Table 7. Comparison with Previous Related Studies

Reference	Method	Object / Dataset	Key Findings / Accuracy	Comparison with Current Study
Choi et al. (2011) [18]	Intelligent Forecasting (ELM, Grey Theory)	Fashion Sales (Volatile Demand)	Traditional statistical methods struggle with high volatility in fashion trends.	Validates our finding that volatility (e.g., in Accessories category) is the main constraint

Shih & Lin (2019) [15]	LSTM	E-Commerce Goods (Short-term demand)	LSTM outperforms Random Forest and SVR in capturing short-term non-linear patterns.	for forecasting accuracy. Extends the application of LSTM from large e-commerce data to offline MSME data, proving its viability for small-scale datasets.
de Castro Moraes et al. (2024) [20]	Hybrid CNN-LSTM	Large Retail Chain (Rossmann Stores)	Hybrid models yield lower error than standalone LSTM by capturing spatial-temporal features.	While [20] uses complex hybrid models for massive datasets, our study proves that Standard LSTM with Cyclical Feature Engineering is sufficient and effective (MAPE <10%) for stable MSME categories without high computational cost. 9.25% (Stable Categories)
Proposed Method (This Study)	LSTM + Cyclical Features	Indonesian Clothing MSME	MAPE 2.51% - 9.25% (Stable Categories)	Tailors the LSTM approach for limited historical data (23 months) using domain-specific preprocessing (month_sin/cos) to capture seasonality.

However, the variation in model performance across categories, particularly lower accuracy in highly volatile categories, provides new perspective on the findings of similar studies in the clothing industry [18], [19]. While these studies report overall accuracy improvements, this study demonstrates that data stability and volume within each category are significant determinants. This indicates that

LSTM success is not uniform, but rather depends heavily on the unique characteristics of each product time series.

Thus, this study adds to the literature by highlighting the practical limitations of applying LSTM to MSME data. While technically capable of producing accurate predictions, the model's effectiveness is heavily influenced by data quality and completeness. This finding also provides important context for the research proposed by [20] on hybrid models, which suggests that even more sophisticated models face similar challenges if the predictive signal in historical data is weak or inconsistent.

The performance patterns observed in this study are consistent with the methodological choices implemented, such as the use of a 12-month sliding window and cyclical seasonal encoding. These design decisions explain why categories with more stable temporal structures, such as Set and Baby & Kids Fashion, achieved higher accuracy, whereas categories with irregular or highly volatile demand exhibited weaker predictive signals. Across all categories, the model's predictions appear smoother than actual data because LSTM inherently captures long-term temporal trends while filtering out short-term fluctuations, especially when trained on limited monthly observations.

From a practical perspective, these findings imply that stable categories are well-suited for data-driven inventory and budgeting decisions, while volatile categories may require complementary strategies or additional external variables not available in the current dataset. This study also highlights the limitations of forecasting with short MSME datasets and suggests that future research may benefit from longer historical records, richer exogenous features, or hybrid deep learning architectures to better capture complex seasonality and event-driven demand spikes.

5. CONCLUSION

This study successfully implemented and evaluated a Long Short-Term Memory (LSTM) model to address sales projection challenges in the clothing industry for MSMEs. Based on a series of experiments and optimizations, this study successfully addressed the identified issues and achieved the desired results.

1. This research successfully developed an LSTM model capable of producing predictions with high accuracy across several key product categories. Categories such as Sets and Baby & Kids Fashion achieved a Mean Absolute Percentage Error (MAPE) below 10%, indicating that this model can be a reliable tool for short- and medium-term business planning.
2. This research successfully revealed that sales patterns vary significantly across categories. Categories with more stable data proved easier to predict, while others exhibited higher volatility. These findings provide a deeper understanding of the varying customer behavior patterns for each product segment, addressing the need for MSMEs to analyze their sales data more effectively.
3. The model's success in achieving high accuracy yields clear strategic recommendations. To improve performance, MSMEs are advised to focus on optimizing stable product categories and increasing the consistency of data collection for more volatile categories.

Overall, this study concludes that the LSTM model is an effective and potential method for forecasting MSME product sales, with the note that its success is strongly supported by the quality of data pre-processing and an understanding of the unique characteristics of each product category.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this article.

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