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Research Article

Artificial Intelligence (AI) using Long Short-Term Memory (LSTM) for Sales Prediction in Campus Minimarkets

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Abstract:
This study applies Artificial Intelligence (AI) using the Long Short-Term Memory (LSTM) algorithm to predict daily sales at the FIKOM-UMI Minimarket. Sales data from 2023 to 2024 involving 82 items were used and processed into a time series format. Five LSTM architectural scenarios were tested, including baseline, bigger model, lightweight, bidirectional LSTM, and single-layer medium, to identify the most effective model in capturing sales patterns. The data underwent preprocessing stages, including daily aggregation, reindexing to fill missing dates, and normalization using MinMaxScaler before being transformed into sequences with a 30-day time step. Model performance was evaluated using MSE, RMSE, MAPE, and accuracy metrics. The results show that the Bidirectional LSTM (Scenario 4) achieved the best performance, with the lowest MAPE of 19.43% and the highest accuracy of 80.57%. The model successfully generated stable predictions for 7-day and 30-day forecasting with a range of 153–155 units per day, indicating consistent sales patterns. Testing on the top 10 best-selling items showed significant performance variation, with GARUDA ROSTA BWNG 100 Gram achieving the highest accuracy (46.97%), while *aoka rasa pandan* showed the lowest performance (-76.05%). These findings demonstrate that the LSTM model can be effectively applied for sales prediction in campus minimarkets; however, a hybrid approach with product segmentation is recommended to optimize inventory management across product categories with varying levels of predictability.

Keywords: Artificial Intelligence; LSTM; Sales Prediction; Minimarket; Deep Learning

Dataset link: https://drive.google.com/file/d/1WAJ3wVWiR-ANnn7O_-UsfmuV4v_vFhfS/view?usp=sharing

1. Introduction

The development of digital technology has driven the widespread adoption of Artificial Intelligence (AI) across various sectors, including retail. One of the main challenges faced by retail businesses is the uncertainty in predicting sales, which has implications for effective inventory management and operational efficiency. The “Gade Gade” Minimarket, managed by the Faculty of Computer Science, Universitas Muslim Indonesia (UMI), faces similar challenges, particularly in projecting demand for dynamic products such as food and beverages. Inaccurate predictions can lead to overstocking, waste, and loss of potential sales due to stock shortages [1], [2]. Therefore, a more adaptive and precise computational approach is required to support optimal inventory management.

Deep learning methods, particularly Long Short-Term Memory (LSTM), have proven effective for time series forecasting due to their ability to recognize historical patterns, seasonal trends, and dynamic changes in consumer behavior. LSTM models can process daily or weekly sales data while considering variables such as academic periods, promotions, and student activities as the primary consumers [3], [4], [5]. With this predictive capability, the implementation of LSTM becomes a strategic solution to improve sales prediction accuracy, enabling more precise and efficient inventory management in campus minimarket environments.

The approach used in this study is a quantitative approach based on historical sales data obtained from the minimarket Point of Sale (POS) system. The research process includes data preprocessing, data exploration, LSTM model development, and model performance evaluation. The evaluation is conducted using several statistical metrics, namely Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and prediction accuracy (%) to provide a comprehensive overview of model quality. All model development and visualization processes were carried out using the Google Colab platform as a cloud-based computational environment [6].

Various previous studies have shown that Artificial Intelligence (AI) and deep learning methods have been successfully applied to sales prediction across different sectors. Studies by Maiyana [1], Belani [2], Zaki [3], Awalloedina et al. [4], Ikhsan et al. [5], Firmansyah and Akbar [6], Desra and Rosnelly [7], Zamroni and Mujilahwati [8], Elyas and Prayoga [9], as well as Rahman [10] and Husein & Lubis [11], demonstrate the successful use of algorithms such as ANN, Bayes, Artificial Neural Networks, Apriori, and data science approaches to improve product demand prediction accuracy. Furthermore, Popoola et al. [12], Khumaidi et al. [13], and Aisyah & Rachmawati [14] emphasize the effectiveness of LSTM and hybrid deep learning models in modeling time series data, both in retail and Internet of Things (IoT) contexts. Overall, these studies strengthen the scientific foundation that LSTM is a relevant, adaptive, and promising method for producing accurate sales predictions at the FIKOM UMI minimarket.

2. Method

Proposed Framework for Minimarket Sales Prediction Workflow

The research workflow begins with the environment preparation stage by importing the required libraries such as pandas, numpy, matplotlib, TensorFlow/Keras, and sklearn, and setting a random seed to ensure reproducibility of results. Next, the data is uploaded and read from a CSV file containing information on date, items sold, and quantity sold into a pandas DataFrame, with the date column converted into datetime format. The data then undergoes aggregation and preprocessing, where sales are grouped by date to obtain total daily sales, followed by reindexing to fill missing dates with zero values to ensure there are no gaps in the time series data. Afterward, the data enters the normalization stage using MinMaxScaler to transform sales values into a range of 0–1, and is then converted into sequences with a 30-day time step as input and the 31st day as the target. The data is subsequently reshaped into a 3D format and split into training (80%) and testing (20%) sets.

At the model architecture definition stage, a function is created to generate five different LSTM model variations, including baseline, bigger, lightweight, bidirectional, and single-layer configurations with different neuron and dropout settings. These five scenarios then undergo sequential training and evaluation using Early Stopping, where each model is used to predict the test set and its performance metrics (MSE, RMSE, MAPE, Accuracy) are calculated. The results of all five scenarios are then presented in a comparison table. Prediction results from all models are visualized in the comparison visualization stage using individual subplots and combined graphs to visually compare their performance. Based on the highest accuracy metric, the best-performing model is selected and retrained on the entire dataset to improve forecasting capability.

The selected best model is then used to perform forecasting for the next 7 and 30 days using a rolling prediction method, where predictions are generated iteratively by updating the input sequence each time a new prediction is produced. The prediction results are then transformed back to the original scale and organized into a complete DataFrame along with the corresponding dates. Subsequently, the forecasting results are visualized in the results visualization stage by displaying graphs that combine historical data with 7-day and 30-day predictions to provide a clear visual representation of future sales trends. Finally, there is an option to save the best model in .h5 format, which can be downloaded for deployment or future use without retraining, allowing the model to be directly applied for prediction on new data. The proposed sales prediction workflow framework is illustrated in **Figure 1**.

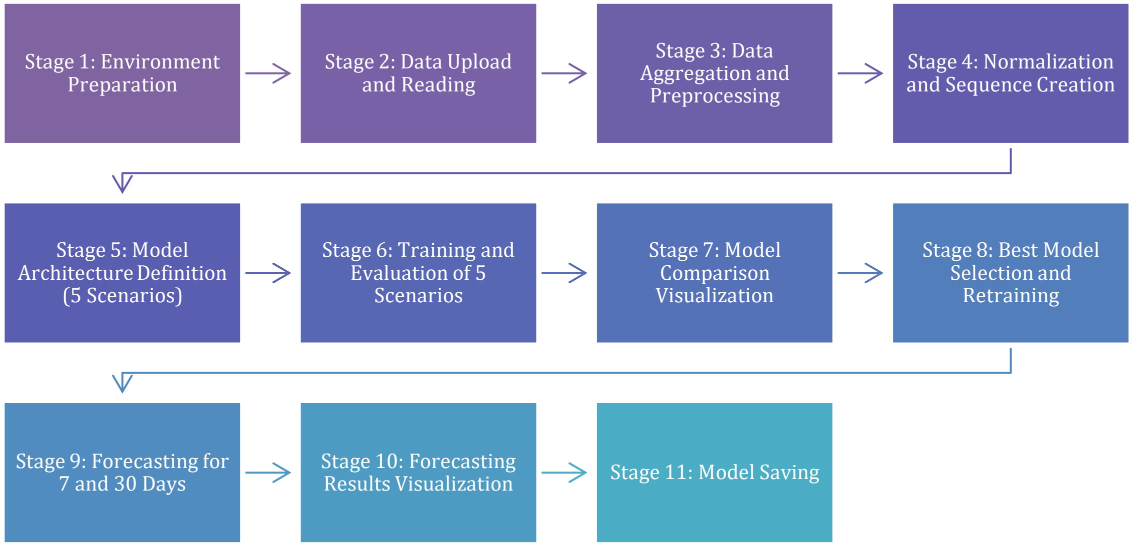

Figure 1. Proposed workflow framework for minimarket sales prediction using LSTM.

LSTM (*Long Short Term Memory Network*)

This study employs an Artificial Intelligence (AI) approach based on the Long Short-Term Memory (LSTM) algorithm, which is an extension of the Recurrent Neural Network (RNN) designed to overcome limitations in learning long-term dependencies in sequential data. The general architecture of LSTM consists of a memory cell, input gate, output gate, and forget gate [12]. Conventional RNNs have limitations in retaining long-term information due to the vanishing gradient problem, which reduces learning capability as the sequence length increases. To address this issue, LSTM was introduced by incorporating memory cells and gating mechanisms that allow the network to retain important information over longer periods in a stable and efficient manner [7], [12], [15]. This structure enables LSTM to maintain gradient flow during the training process, thereby improving the network's ability to learn complex temporal patterns compared to conventional RNNs [4], [8], [16], [17].

Architecturally, LSTM consists of several main components, namely the memory cell, input gate, forget gate, and output gate, which work together in an integrated manner to regulate the flow of information within the network. The memory cell functions as a long-term information storage unit, while the input gate is responsible for controlling new information that enters the memory cell. The forget gate determines which information should be retained or discarded based on its relevance to the current state, while the output gate controls the information that will be used as the output of the LSTM unit and passed to the next layer [7], [12], [15]. This mechanism enables LSTM to preserve important information, reduce the accumulation of irrelevant information, and improve learning stability during the training process [16], [18], [19].

The main advantage of LSTM lies in its ability to model complex and nonlinear temporal relationships in time series data. LSTM can effectively capture both short-term and long-term dependencies, resulting in more accurate prediction performance compared to conventional methods and traditional machine learning algorithms [1], [5], [6], [11], [20]. In addition, LSTM has been proven effective in various applications such as traffic prediction, energy consumption prediction, financial forecasting, electrical load prediction, as well as various sensor-based monitoring systems and Internet of Things (IoT) applications [5], [11], [21], [22], [23], [24].

The LSTM cell operates by receiving input at each time step and processing it using gating mechanisms to determine which information should be stored, updated, or removed from the memory cell. This process allows LSTM to adaptively adjust its internal representation according to changes in temporal patterns within the data. With this capability, LSTM can generate better feature representations and significantly improve prediction accuracy compared to conventional methods [6], [19], [20], [25], [26]. Therefore, LSTM has become one of the most widely used deep learning algorithms in modern research, particularly in time series prediction, sensor-based intelligent systems, and Artificial Intelligence applications that require accurate and efficient temporal data analysis [8], [17], [19], [26]. The LSTM architecture, consisting of the memory cell, input gate, forget gate, and output gate, is illustrated in **Figure 2**.

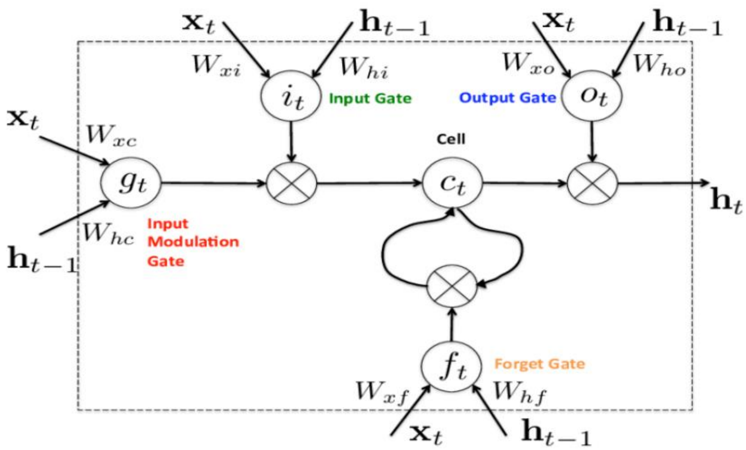

Figure 2. The General Architecture of the Long Short-Term Memory (LSTM) Network [27], [28], [29], [30]

The data entering the forget gate is processed according to its information, and relevant data is selected to be retained in the memory cell. The activation function used is sigmoid. Equation (1) describes its working principle. Meanwhile, the input gate consists of two gates that use the sigmoid activation function to update information and the tanh activation function to store new values in the memory cell [27]. This process can be represented by Equations (2) and (3).

$$f_t = \sigma\left(W_f[h_{t-1}, x_t]\right) + b_t \tag{1}$$

$$i_t = \sigma\left(W_i[h_{t-1}, x_t]\right) + b_i \tag{2}$$

$$c_t = \tanh(W_i[h_{t-1}, x_t]) + b_c \tag{3}$$

Equation (4) represents the combined result of the values from the input gate. The forget gate will update the memory cell value using the cell gate values. In the output gate, there are also two gates: one to determine the value to be output using the sigmoid activation function, and another to store the value using the tanh activation function. This process is formulated in Equations (5) and (6).

$$c_t = f_t * c_{t-1} + i_t * \acute{c}_t \tag{4}$$

$$o_t = \sigma\left(W_0[h_{t-1}, x_t]\right) + b_0 \tag{5}$$

$$h_t = o_t\, tanh \tanh(c_t) \tag{6}$$

LSTM Model Testing Scenarios

Table 1. Testing Scenarios

Scenario	Model Architecture	Testing Objective
Scenario 1: Baseline	LSTM(64, return_sequences=True) → Dropout(0.2) → LSTM(32) → Dense(1)	Serves as the baseline model for comparison; balanced between model capacity and training speed.
Scenario 2: Bigger Model	LSTM(128) → Dropout(0.3) → LSTM(64) → Dense(1)	Tests a high-capacity model to capture long or complex patterns; higher risk of overfitting.

Scenario	Model Architecture	Testing Objective
Scenario 3: Lightweight	LSTM(32, return_sequences=True) → Dropout(0.1) → LSTM(32) → Dense(1)	Lightweight model, fast to train, suitable for small datasets or rapid prototyping.
Scenario 4: Bidirectional LSTM	Bidirectional(LSTM(64)) → Dropout → Bidirectional(LSTM(32)) → Dense(1)	Provides bidirectional sequence processing to capture complex recurring patterns; produces more precise predictions.
Scenario 5: Single-layer Medium	LSTM(50) → Dense(1)	Simplest model; stable and effective for sales patterns that are not highly fluctuating.

Table 1 presents the testing scenarios of five LSTM model architectures. The first scenario represents the baseline model, which uses two LSTM layers with 64 and 32 units, respectively. This model serves as the initial reference for comparing the performance of the other scenarios. The second scenario is a larger-capacity model with LSTM layers of 128 and 64 units, designed to evaluate whether increasing the number of neurons can capture more complex long-term patterns. However, the performance of this model tends to decline because the relatively small dataset does not support the large model capacity requirements.

The third scenario is a lightweight model consisting of two LSTM layers with 32 units each. This architecture achieves fairly competitive performance despite having significantly fewer parameters, indicating that minimarket sales data does not require excessively high model complexity. Meanwhile, the fourth scenario employs a Bidirectional LSTM approach, which processes data in both forward and backward directions, enabling it to better recognize recurring patterns. The fifth scenario is a simple single-layer LSTM model with 50 units, evaluated to determine whether a minimalistic model can produce stable results.

3. Result and Discussion

Result

This study uses daily sales data from the FIKOM–UMI Minimarket from 2023 to 2024, covering a total of 82 items, which were aggregated into time series data for prediction purposes. In general, the sales pattern in the minimarket shows relatively stable characteristics. All data were then normalized using the MinMaxScaler method to ensure a more optimal and consistent model learning process. After the preprocessing stage, this study evaluated five LSTM model scenarios with different levels of complexity to identify the most effective architecture for predicting daily sales patterns.

Table 2. Scenario Testing Results

Scenario	MSE	RMSE	MAPE (%)	Accuracy (%)
1	1194.67016	34.564001	20.110002	79.889998
2	1230.1789	35.073906	21.07055	78.92945
3	1181.42782	34.371905	20.389586	79.610414
4	1183.83889	34.40696	19.427266	80.572734
5	1186.75171	34.449263	20.371378	79.628622

Table 2 presents the results of testing the five scenarios. Based on the results, the fourth scenario, namely the Bidirectional LSTM, achieved the best performance compared to all other scenarios. This model produced the lowest MAPE error rate of 19.42% and the highest accuracy of 80.57%. This indicates that bidirectional processing provides significant advantages in understanding sequential daily sales patterns. The baseline and lightweight models (Scenarios 1, 3, and 5) showed relatively similar performance, with accuracy levels ranging from 79% to 80%, indicating that stable data patterns can be effectively predicted using architectures that are not overly complex. In contrast, the high-capacity model in Scenario 2 experienced a decrease in accuracy due to a tendency toward overfitting, as the amount of data was not proportional to the model complexity.

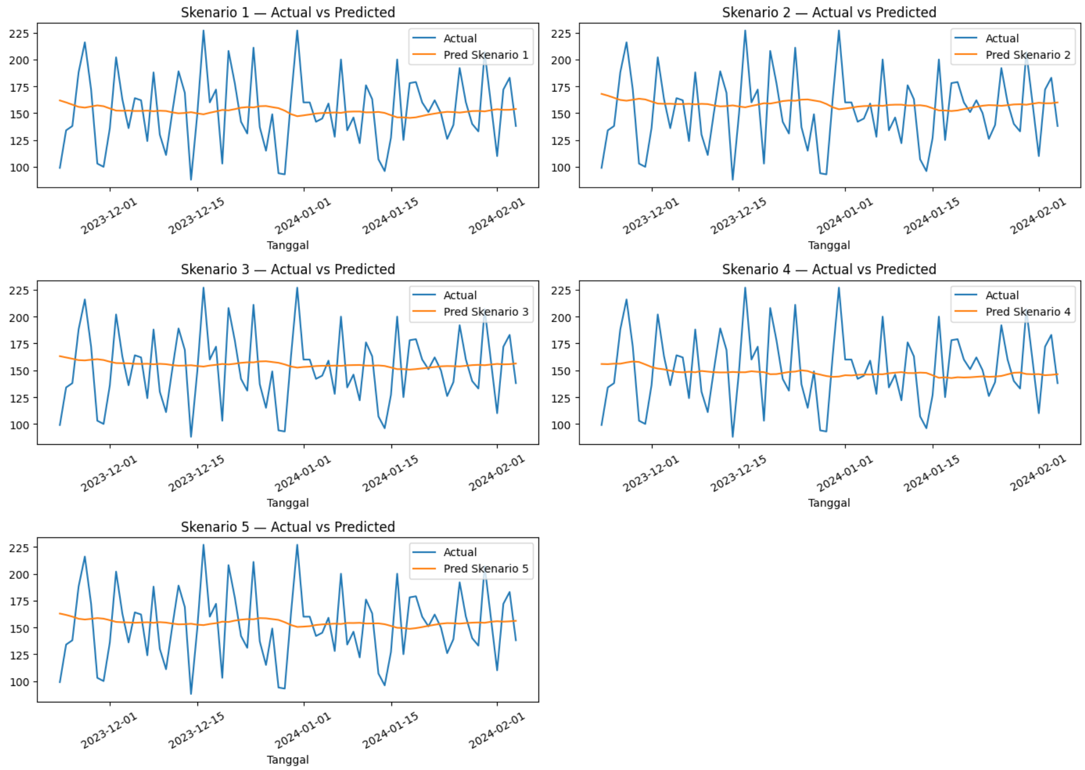

Figure 3. Graph of the Results of the Five Testing Scenarios

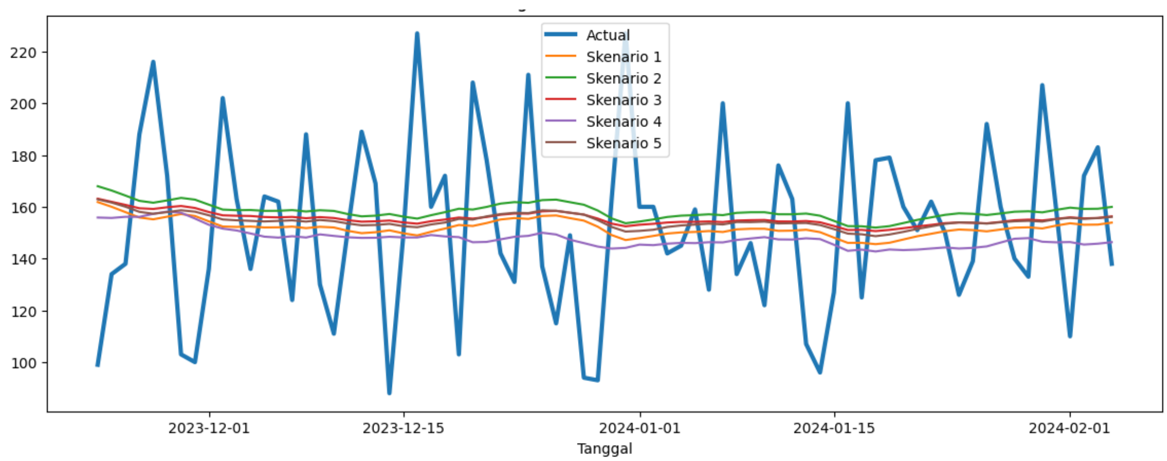

Figure 4. Comparison of Scenarios 1 to 5 for Sales Prediction

Figures 3 and 4 present a comparison between the actual data and the predicted results from the five tested LSTM model scenarios, namely Scenario 1 through Scenario 5. In all graphs, the actual daily sales pattern exhibits highly dynamic fluctuations, with sharp changes in values from day to day, while the prediction lines from each scenario show much smoother and more stable patterns. This indicates that all LSTM models tend to capture the general trend rather than the random daily variations.

However, there are differences in accuracy levels among the scenarios. Scenario 4 (Bidirectional LSTM) appears to provide prediction lines that are closer and more responsive to changes in the actual pattern compared to the other four scenarios, which is consistent with the quantitative evaluation results that identified it as the best-performing model. Meanwhile, Scenario 2 (the larger model) appears slightly more rigid and less capable of following changes in the data, indicating signs of overfitting and difficulty adapting to rapidly fluctuating data.

Overall, these testing results show that although all models are capable of capturing the general trend of the data, the Bidirectional LSTM is more representative of the dynamic sales patterns, whereas the other models tend to provide smoother average estimates that are less adaptive to daily variations.

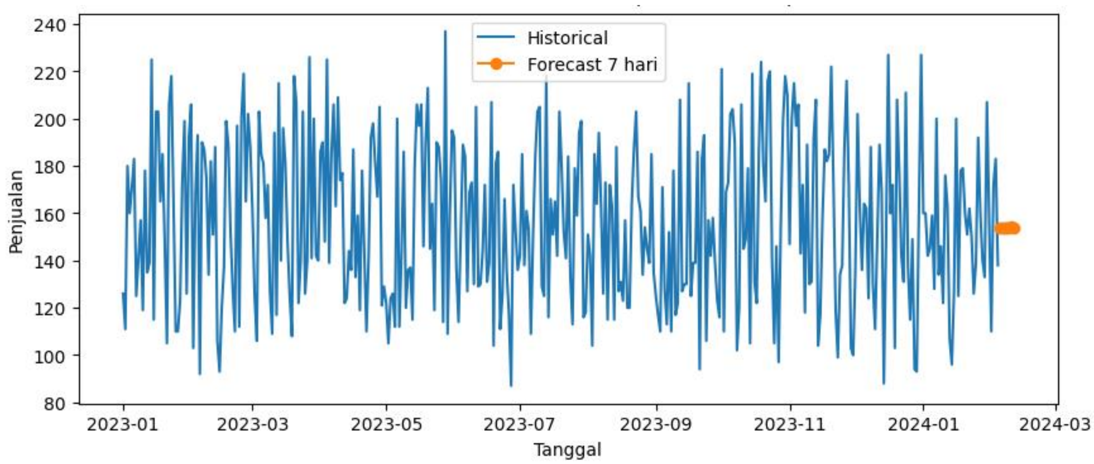

Figure 5. Seven-Day Ahead Prediction Using the Best Model

Figure 5 shows a comparison between the historical sales data of the FIKOM-UMI minimarket throughout 2023 to early 2024 and the seven-day ahead prediction results using the best model, namely the Bidirectional LSTM scenario. The historical data appears highly fluctuating, with significant daily sales variations, reflecting unstable demand dynamics. On the right side of the graph, the orange points represent the seven-day forecast, which appear smoother and more stable compared to the historical pattern, with values ranging from approximately 153 to 154 units.

This indicates that the model is capable of capturing the general sales trend without being overly influenced by daily noise, resulting in projections that are conservative and stable. The relatively flat prediction pattern suggests that the model prioritizes short-term trends rather than extreme variations, thereby providing reliable estimates for short-term inventory planning in the minimarket.

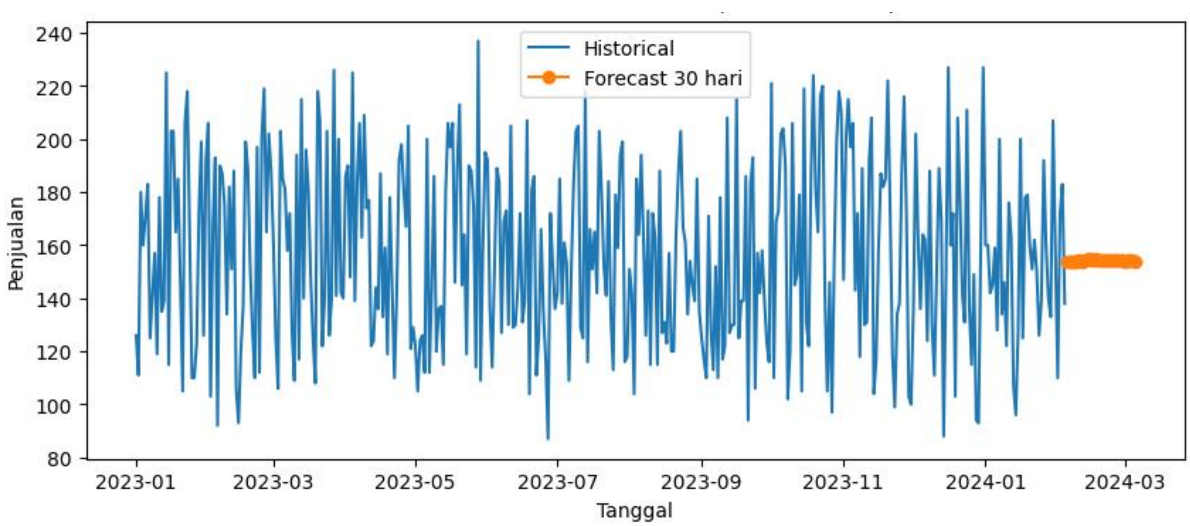

Figure 6. Thirty-Day Ahead Prediction Using the Best Model

Figure 6 presents a comparison between historical sales data (blue line) from January 2023 to February 2024 and the LSTM model's prediction results for the next 30 days (orange line). The historical data shows highly dynamic sales fluctuations, ranging from 80 to 240 items per day, reflecting high volatility likely influenced by weekly patterns, holidays, and special events such as promotions or payday periods. In contrast, the model's prediction results appear nearly flat at around 154 items per day, with very small variations. This indicates that the model captures the long-term average sales but is unable to predict significant daily fluctuations as observed in the actual data. This suggests that although the model achieves an accuracy of 80%, it tends to produce conservative predictions close to the mean value and has not yet fully captured complex volatility patterns. Therefore, for practical applications in minimarket inventory management, the model needs to be improved by incorporating external features such as day-of-week information, holidays, or promotional events to better anticipate potential extreme increases or decreases in sales.

The sales prediction for the next 7 days shows very stable values in the range of 153 to 154 units per day. The variation between days is minimal, reinforcing that daily minimarket demand is relatively constant and not influenced by specific anomalies. Similarly, the 30-day forecast shows a nearly identical pattern, with slight fluctuations but still remaining within a very narrow range, between 153.6 and 154.7 units per day. This indicates that the daily sales pattern in the minimarket follows a flat trend, without significant seasonal patterns or trend shifts. The stability of this pattern demonstrates that the LSTM method is highly suitable for this type of data, particularly due to the relatively consistent time series characteristics.

Table 3. Best-Selling Items Based on Total Item Sales

No	Item
1	*Kalpa Wfr Cklt klp24g*
2	*Regal Marie Duo Vanilla 20g*
3	*Roma Bisc Kelapa 300g*
4	*Nipis Madu 330 ml*
5	*aoka nenas*
6	*aoka rasa pandan*
7	*Sprstar Snp Wfr 12'S*
8	*Oishi Pop Corn Chocolate 100g*
9	*GARUDA ROSTA BWNG 100 Gram*
10	*Nutriboost orange flavour 300ml*

Table 4. Testing Results of Top-Selling Items Using the Best Model

No	Item	MSE	RMSE	MAPE	Accuracy (%)
1	*Kalpa Wfr Cklt klp24g*	18.31698	4.279834	86.12568	13.87432
2	*Regal Marie Duo Vanilla 20g*	11.0249	3.320376	103.2205	-3.22047
3	*Roma Bisc Kelapa 300g*	5.044361	2.245965	89.99749	10.00251
4	*Nipis Madu 330 ml*	6.938494	2.634102	63.87171	36.12829
5	*aoka nenas*	19.21727	4.38375	97.14786	2.852136
6	*aoka rasa pandan*	11.30765	3.362685	176.0486	-76.0486
7	*Sprstar Snp Wfr 12'S*	7.700127	2.77491	106.2361	-6.23611
8	*Oishi Pop Corn Chocolate 100g*	6.065913	2.462907	70.03332	29.96668
9	*GARUDA ROSTA BWNG 100 Gram*	8.400694	2.898395	53.02552	46.97448
10	*Nutriboost orange flavour 300ml*	7.893728	2.809578	56.96736	43.03265

Table 3 presents the top 10 best-selling items based on historical sales transaction records. Each item was then analyzed using the LSTM model to predict short-term (7 days) and medium-term (30 days) sales. With this approach, the model's performance was evaluated in capturing demand patterns for high-rotation products (fast-moving items). **Table 4** presents the accuracy evaluation results, including MSE, RMSE, MAPE, and Accuracy (%), allowing identification of items with stable and fluctuating sales patterns. Some products, such as GARUDA ROSTA BWNG 100 Gram, Nipis Madu 330 ml, and Nutriboost Orange Flavour 300 ml, demonstrated better prediction performance, with relatively low MAPE values and higher accuracy. In contrast, items such as aoka rasa pandan showed high MAPE values, indicating unstable sales patterns or patterns that are difficult for the model to predict.

This top-selling item evaluation used the best LSTM model (Scenario 4: Bidirectional LSTM) on the 10 highest-selling products at the FIKOM-UMI Minimarket, and the results revealed very significant performance variations across product categories, with accuracy ranging from -76.05% to 46.97%. The best-performing product was GARUDA ROSTA BWNG 100 Gram, with an accuracy of 46.97% and MAPE of 53.03%, followed by Nutriboost Orange Flavour 300 ml (43.03%) and Nipis Madu 330 ml (36.13%). This indicates that savory snacks and functional beverages tend to have more stable and predictable sales patterns due to relatively consistent consumption. Conversely, products with poor or even negative performance included aoka rasa pandan, which had the lowest accuracy of -76.05% and MAPE of 176.05%, followed by Sprstar Snp Wfr 12'S (-6.24%) and Regal Marie Duo Vanilla 20 g (-3.22%). This suggests that biscuits, wafers, and fruit-flavored beverages have highly irregular purchasing patterns, likely influenced by impulsive buying behavior and inconsistent stock availability.

An interesting finding from this analysis is the paradox of top-selling items, where Kalpa Wfr Cklt klp 24 g, ranked as the number one best-selling product, achieved only 13.87% accuracy, while GARUDA ROSTA, ranked ninth, achieved the highest accuracy. This demonstrates that sales volume does not necessarily correlate with the predictability of a product.

Discussion

These results indicate that the LSTM model is not universally suitable for all products, and therefore a hybrid approach with segmented strategies is required. This includes using AI-based forecasting for Category A products with accuracy above 35% (GARUDA ROSTA, Nutriboost, Nipis Madu), combining LSTM with a 30–40% safety stock strategy for Category B products with accuracy between 10% and 35% (Oishi, Kalpa Wfr, Roma Bisc), and applying intermittent demand methods such as Croston’s method or manual override for Category C products with accuracy below 10% (aoka, Regal Marie, Sprstar). To improve model performance, it is recommended to incorporate specific feature engineering, such as day-of-month information to capture payday effects, campus events such as exam periods or semester breaks, weather data that may influence beverage sales, and promotion and discount tracking that may cause unexpected sales spikes. These enhancements would allow the model to more accurately capture volatility and complex patterns across different product categories.

Overall, the results of this study demonstrate that the LSTM-based Artificial Intelligence model is capable of providing sufficiently accurate and reliable sales predictions. Bidirectional LSTM was proven to be the best-performing model, followed by the other model configurations. This finding confirms that model performance is not determined solely by the number of neurons, but also by the suitability of the architectural structure to the characteristics of the data. The model’s success in generating stable predictions provides a strong foundation for developing decision support systems in campus minimarket environments.

4. Conclusion

Based on the results of this study on the application of Artificial Intelligence (AI) for sales prediction at the FIKOM–UMI Minimarket, it can be concluded that the LSTM model can be effectively used to predict daily sales patterns. Among the five architectural scenarios tested, the Bidirectional LSTM achieved the best performance, producing the lowest error rate and the highest accuracy of 80.57%. The performance of the other models, including the baseline and lightweight models, also demonstrated stable results, reinforcing the finding that minimarket sales patterns are relatively easy to learn using LSTM-based models. Predictions for the 7-day and 30-day periods showed consistent sales patterns, ranging between 153 and 155 units per day. These prediction results have strong potential to support stock planning, inventory management, and operational decision-making in the minimarket. Furthermore, this study demonstrates that AI models can serve as effective analytical tools to support retail management in the context of educational institutions.

Several recommendations can be proposed for future research. First, prediction accuracy can be improved by incorporating external variables such as campus events, holidays, promotional activities, weather conditions, and different item categories, allowing the algorithm to learn the influence of these factors on sales patterns. Second, the amount of historical data can be expanded to cover 3-5 years, enabling more comprehensive detection of annual seasonal patterns. Third, future studies may explore hybrid models such as CNN-LSTM, GRU, or Transformer, which are becoming the new standard in time series processing. Fourth, the research results can be implemented in the form of a real-time prediction dashboard that can be used by minimarket management to monitor demand and optimize inventory. Finally, future research may also consider category-based prediction approaches, as each product type may exhibit different demand patterns and require specialized models. With these further developments, the application of AI in retail management will become more advanced and provide greater strategic benefits for the operational management of the FIKOM–UMI minimarket.

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