Food Product Sales Forecasting Using the LSTM Model: A Case Study of SMAN 1 Malang Teachers' Cooperative

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Abstract

The SMAN 1 Malang Teachers' Cooperative manages consigned food products from local partners but faces fluctuating daily sales and the lack of an accurate forecasting system, which often results in stock shortages or surpluses. This study aims to develop a sales prediction model using a deep learning-based Long Short-Term Memory (LSTM) algorithm to improve forecasting accuracy and procurement efficiency. The developed system utilizes historical transaction data from the cooperative from January 2024 to December 2024, which is converted into time series data. The research stages include data preprocessing with interpolation, rolling mean smoothing, time feature engineering, normalization using MinMaxScaler, and model training using a two-layer LSTM architecture with a fully connected layer (hybrid). Model optimization uses EarlyStopping and ReduceLROnPlateau to prevent overfitting. Model evaluation is conducted separately using the Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) metrics. The test results show that the optimized hybrid LSTM model achieved an average accuracy of 88.19% with an MAPE value of 11.81%, an MAE of 1.29, an MSE of 6,63, and an RMSE of 1.70. These values indicate that the model has stable, accurate, and adaptive predictive capabilities in estimating daily sales for various consignment food products managed by the SMAN 1 Malang Teachers' Cooperative.

1. Introduction

Fluctuations in demand are a fundamental challenge in supply chain management and retail operations (Mera & Ernawati, 2023). For the SMAN 1 Malang Teachers' Cooperative, this challenge is even more complex because most of the products it manages are consignment foods, which generally have a short shelf life (Putri & Sadikin, 2021). The inability to accurately predict daily sales can lead to two major financially detrimental problems, namely overstocking and stockouts, which risk causing lost sales potential, expired or damaged products, and decreased customer satisfaction (Hurtado-Mora et al., 2024; Radite Putra & Hendry, 2022).

Academic literature indicates that accurate sales forecasting systems play an important role in maintaining the balance between supply and demand, as well as supporting data-driven decision-making in the retail sector (Ajiboye, 2024; Ashari & Sadikin, 2020). With the increasing complexity of consumer purchasing patterns and seasonal factors, traditional statistical methods such as ARIMA are often unable to capture the nonlinear relationships in sales data over time (Nendi Sunendar et al., 2025; Susilo et al., 2025). In this context, the deep learning approach, particularly Long Short-Term Memory (LSTM), is the preferred choice due to its ability to learn long-term dependencies and dynamic variability in sales data (Luo et al., 2022; Pliszczuk et al., 2021; Wang et al., 2021).

The novelty of this research lies in its empirical implementation and in-depth analysis of the application of the LSTM–MLP hybrid model in the operational environment of educational cooperatives in Indonesia. This research fills this gap by developing and rigorously evaluating the LSTM–MLP hybrid model for daily sales forecasting at the SMAN 1 Malang Teachers' Cooperative. The main contributions of this research include three aspects, namely implementing the optimized LSTM-MLP model optimized to process smoothed sales data with temporal engineering features, followed by performance evaluation at the aggregate level and in-depth performance variance analysis for each product, as well as identifying factors such as data volatility that distinguish products with high predictability levels with an accuracy above 90% and low levels with an accuracy of less than 50%. Thus, the results of this study are expected to provide practical guidance for cooperative managers in understanding the reliability and limitations of applying models to the development of adaptive and applicable sales forecasting systems for educational cooperatives in Indonesia (Ormrod, 2024; Yulianto & Latifah, 2024).

1.1 Literature Review

In the field of time series forecasting, particularly in the context of sales prediction, the Long Short-Term Memory (LSTM) model has been a major focus over the past five years (Budiprasetyo et al., 2023; Fitriana et al., 2025). LSTM is known as a recurrent neural network (RNN) architecture that can effectively learn long-term dependencies in nonlinear time series data (Hurtado-Mora et al., 2024; Zhang et al., 2023). This advantage has made LSTM popular for sales forecasting, but its performance in the real world is not always consistent because it is influenced by data quality, the number of features, and model configuration (Ahmad et al., 2024; Susilo et al., 2025). Therefore, it is necessary to evaluate and synthesize the latest literature to identify gaps, inconsistencies, and controversies related to LSTM performance in sales forecasting.

Research by Susilo et al. (2025) shows the best scenario in which a multivariate LSTM model with contextual features such as stock, price, and discount achieves high accuracy (MAPE 3.60%) in predicting sales in distribution companies. Meanwhile, a more realistic approach is demonstrated by Fitriana et al. (2025), who applied LSTM to daily chicken meat sales data with fluctuating patterns. Their research results show a MAPE of 17.17% with an optimal time window of 14 days. Other studies by Cahyani et al. (2023) and Muhammad & Nurhaida (2025) also emphasize the importance of feature scaling strategies and training data composition in improving LSTM model performance.

A synthesis of these studies indicates that LSTM performance can vary extremely depending on methodological design, data quality, and model complexity (Filali et al., 2022; Roosaputri & Dewi, 2023). This fact shows that simply using LSTM does not guarantee superior performance. Furthermore, most previous studies only report aggregate values (such as average MAPE) without exploring performance variance between products within a single dataset.

However, most previous studies only reported average model results without conducting an in-depth analysis of performance variations between products in a single dataset. This gives rise to what is known as the LSTM performance dilemma, a phenomenon in which models perform well on some data but fail to maintain consistency across all product categories (Venkiteela, 2025).

To address this gap, this study adopts and adapts a hybrid LSTM–MLP architecture, then implements it directly on cooperative transaction data. This approach focuses not only on aggregate performance testing but also on granular empirical analysis of model performance variations based on the sales characteristics of each product, which includes identifying distinguishing factors between products with high predictability (>99%) and products with low predictability (<50%). This study provides an applied and contextual contribution to the application of deep learning technology in operational decision-making in educational cooperatives (Kannadasan, 2025).

2. Research Methods

This study utilizes a quantitative methodology based on deep learning, following structured steps. It primarily adheres to the principles of transparency and replicability, as recommended in modern applied scientific research by Ormrod (2024) and Rainio et al. (2024). The method used focuses on developing a hybrid LSTM-MLP model to predict daily sales in a school cooperative environment (Ashari & Sadikin, 2020). The steps are visualized in a research flow diagram shown in Fig. 1.

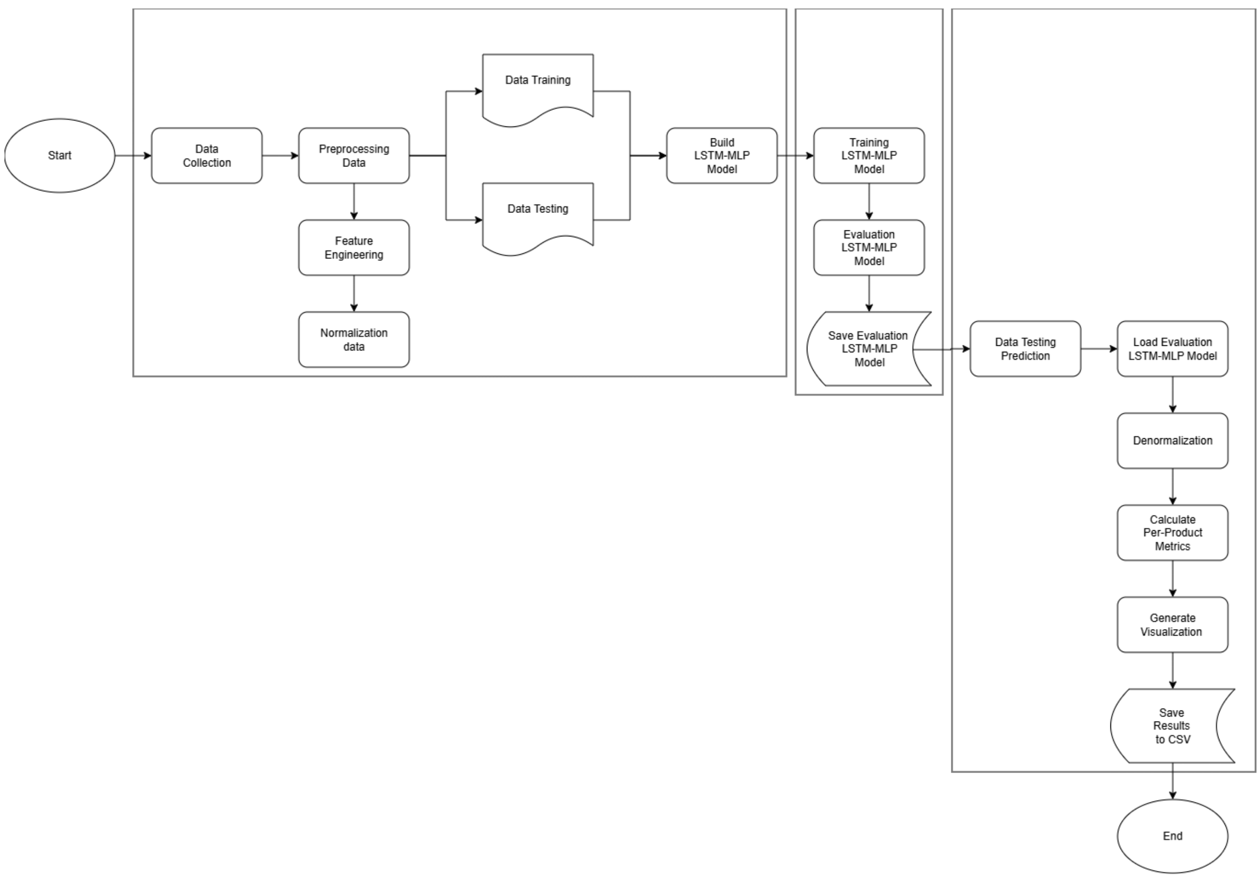

Fig. 1 System Flowchart Figure

2.1 Data Collection and Research Context

This study uses historical transaction data from the SMAN 1 Malang Teachers' Cooperative. The data set includes all daily sales transactions for consignment food products during a one-year period, from January 1, 2024, to December 19, 2024. The unit of analysis used is the total daily quantity sold for each individual product (Pranoto & Majid, 2024). Table 1 is an example of the sales dataset used. The attributes in the dataset include the date, which serves as a daily time identifier; the product, which indicates the identity of each item sold; and the quantity sold (Qty sold), which represents the total sales quantity of each product per day.

Table 1. Sales Dataset Table

No	Date	Product	Sold Qty
1	02/01/2024	Mochi Bites Mbak Nasya12	15
2	02/01/2024	Pisang Coklat Bu Mud	10
3	02/01/2024	Tahu Mercon Bu Mud	43
...	...	...	...
3089	19/12/2024	Zuper Krim Ckt Sari Roti	3
3090	19/12/2024	Zuper Krim Keju Sari Roti	1

2.2 Data Preprocessing

In time series forecasting, raw transaction data is not suitable for direct use. This is because there is still a possibility that the data will prevent the model from working optimally. Therefore, a series of systematic data preprocessing steps needs to be applied to each product:

1. **Resampling and Interpolation**
   Transaction data is grouped and summed based on daily frequency. Daily sales data, such as holidays or days without transactions, are filled in using linear interpolation, thereby creating continuous time series data (Filali et al., 2022; Zhang et al., 2023).

2. **Data Smoothing**
   To reduce short-term fluctuations, a rolling mean with a 3-day window is applied to the sales data. This creates a new variable called Qty_smooth. In addition to reducing short-term noise, this technique serves to highlight the underlying trends in volatile sales data (Fitriana et al., 2025).

3. **Time Feature Engineering**
   Cyclical elements are extracted from the date index and divided into three categories: dayofweek (weekday), month (month of the year), and week. This is done to offer temporal context, which will aid the model in recognizing seasonal trends (Puteri, 2023).

4. **Normalization**
   All relevant features, such as smoothed sales data and engineered temporal features, are scaled to the range [0, 1] using MinMaxScaler. This step is crucial for neural network performance, as it stabilizes the training process and ensures that all features contribute proportionally (Ashari & Sadikin, 2020; Susilo et al., 2025).

5. **Windowing**
   After all features were normalized, the dataset was converted to a supervised learning format using a windowing technique with a window size of 14 days, meaning that the model would use data from the last 14 days to predict the next day's sales value (Fitriana et al., 2025).

2.3 Development of Hybrid LSTM-MLP Models

A hybrid deep learning model was developed by combining a stacked Long Short-Term Memory (LSTM) network with a Dense Layer or Multi-Layer Perceptron (MLP). The architectural design used follows the optimal structure applied by Susilo et al. (2025) and Filali et al. (2022) in their research. This model has an input shape with a window size of 14 and was trained for 100 epochs with 32 samples in each batch. It then has a first layer consisting of an LSTM with 128 units and return_sequences=True, followed by a Dropout layer with a rate of 0.05 to reduce overfitting. Next, a second LSTM layer with 64 units and return_sequences=False is used.

Thereafter, two dense layers (MLP) were added sequentially, each with 64 units and 32 units, both using the ReLU activation function. The output layer consisted of 1 unit that produced the final prediction value. The model is compiled using the Adam optimizer with a learning rate of 0.001 and mean squared error (MSE) as the loss function. To ensure replicable results, the random seed is set using tf.random.set_seed(42). This model is implemented using TensorFlow 2.13 and tested through time-series-based cross-validation on a Google Colab GPU T4 environment.

2.4 Evaluation and Measurement

To assess the feasibility, reliability, and validity of the model, a rigorous evaluation strategy was applied to the data, which included:

1. **Model Validation**
   The windowed data set for each product is divided chronologically into 85% training data and 15% test data. The model performance reported in the training study is calculated exclusively using previously unseen test data.

2. **Training Optimization**
   To prevent overfitting and improve model reliability, two main callbacks are used during the training process. First, EarlyStopping, which monitors validation loss and automatically stops training if there is no improvement in performance for 25 epochs, also has a function to return the best model weights (Yanti et al., 2024). The second is ReduceLROnPlateau with an adaptive function to reduce the learning rate by a factor of 0.7 if the validation loss does not improve for 10 epochs, with a minimum learning rate of 1e-5 (Ahmad et al., 2024).

3. **Evaluation Metrics**
   The predictive accuracy of the model is measured using four standard regression metrics recommended in modern forecasting literature (Rainio et al., 2024). First, Mean Absolute Percentage Error (MAPE) is used to measure the average percentage error and provides an overview of the error rate relative to the actual value. Second, Mean Absolute Error (MAE) measures the average magnitude of error in quantitative units, providing a more intuitive interpretation of the deviation of predictions from actual realizations. Third, Root Mean Squared Error (RMSE) describes the standard deviation of errors and penalizes large errors more heavily. Fourth, Mean Squared Error (MSE) is the average of the squared errors and is used both as a loss function in the model compilation process and as an evaluation metric. The final accuracy value is calculated using the formula (100 – MAPE) to show the accuracy level of the model prediction.

3. Result and Discussion

This section presents an evaluation of the performance of the hybrid LSTM-MLP model that has been developed to validate its effectiveness in predicting daily sales at the SMAN 1 Malang Teachers' Cooperative. Overall, the test dataset evaluation confirms the model's strong predictive capabilities. The optimized hybrid LSTM-MLP model achieved an overall average accuracy of 88.19%, with a MAPE of 11.81%, MAE of 1.29, MSE of 6.63, and RMSE of 1.70. These aggregate results indicate that the model has high and stable accuracy. With a low prediction error rate, this indicates that the model is consistent with previous research findings that demonstrate the consistency of LSTM on sales data.

3.1 Specific Performance per Product

Although the overall average is strong, model performance varies greatly between products, as models depend on the volatility and unique sales patterns of each product. Furthermore, the model performance for each product is ranked to identify which products are predicted most accurately. Table 2 shows a sample of the performance rankings. This table not only highlights the differences in accuracy based on percentage (Accuracy/MAPE) but also the drastic differences in the magnitude of absolute error as indicated by the MSE, RMSE, and MAE metrics.

Table 2. Performance Rankings Table

Rangking	Product	MSE	RMSE	MAE	MAPE	Accuracy
1	Sand Bluberry II Sari Roti	6.553228e-07	0.000810	0.000634	0.063393	99.936607
2	Sand Srky Mdn II Sari Roti	2.328464e-04	0.015259	0.005743	0.456225	99.543775
3	Sand Keju II Sari Roti	5.037074e-04	0.022443	0.013118	1.141782	98.858218
...	...	...	...	...	...	...
36	Spicy Roll Mbak Keyla	3.145139e+01	5.608154	4.414971	53.079378	46.920622

Furthermore, Table 3 provides a sample of granular evaluations of the test data. This detailed view shows how each metric is applied to each forecast made. For example, on 19/12/2024, the model predicted a number of 18.33 for the product 'Tempura Bu Poetoe', which, when compared to the actual data, only had a difference of 0.33, resulting in a very low error with a MAPE of only 1.82%. In contrast, on 23/04/2024, the product 'Mochi Bites Mbak Nasya12' with real data of 4 obtained a prediction of 6.74, showing that the prediction had a large inaccuracy in the MAPE evaluation, namely 68.53%. This granular data is used to calculate the aggregate metrics in Table 2.

Table 3. Granular Test Evaluation Table

No	Date	Product	Actual Qty	Predicted Qty	Prediction Difference	MAPE
1	23/04/2024	Mochi Bites Mbak Nasya12	4	6,74	2,74	68,53
2	24/04/2024	Mochi Bites Mbak Nasya12	10	6,75	-3,25	32,49
3	25/04/2024	Mochi Bites Mbak Nasya12	6	6,75	0,75	12,55
...	...	...	...	...	...	...
433	19/12/2024	Tempura Bu Poetoe	18	18,33	0,33	1,82
434	19/12/2024	Zuper Krim Ckt Sari Roti	3	2,2	-0,8	26,83
435	19/12/2024	Zuper Krim Keju Sari Roti	1	1,78	0,78	78,26

To better understand the performance differences in the existing granular evaluation, a visual analysis of the best- and worst-case predictions of the predicted products is presented. Fig. 2 illustrates the high-accuracy prediction for the product 'Sand CKT II Sari Roti', which ranks 8th with an accuracy of 95.76%. The prediction results closely follow the original data with near-perfect density during the testing period. The model demonstrates high reliability and successfully learns the product's sales patterns, including daily trends and fluctuations.

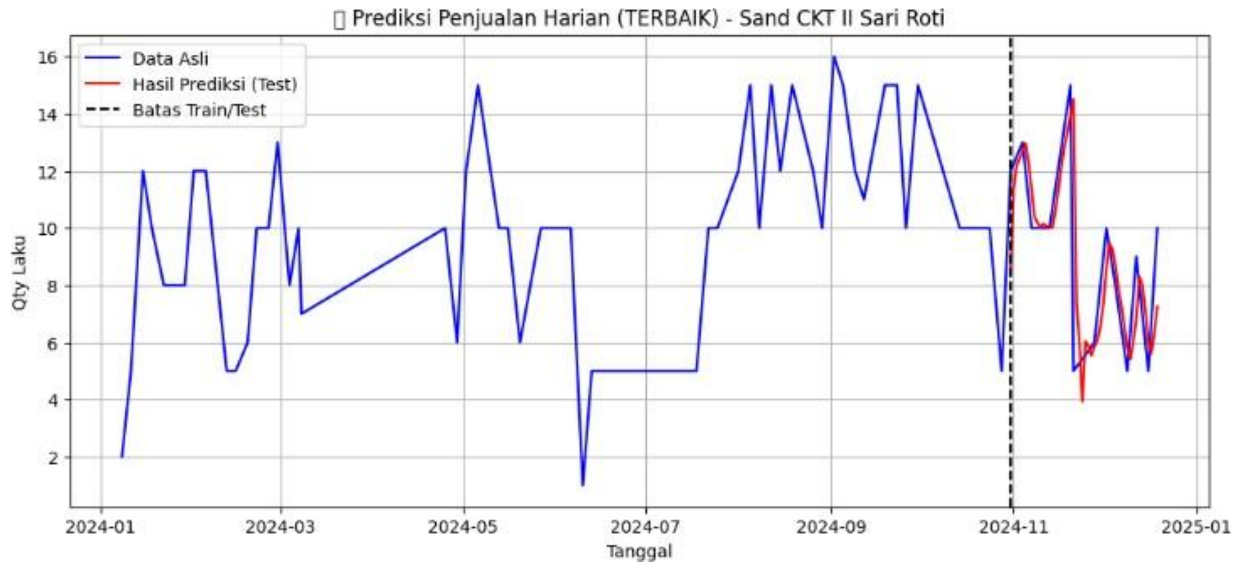

Fig. 2 High-Accuracy Prediction Figure

Conversely, Fig. 3 shows the model's performance for the lowest-ranked product, namely 'Spicy Roll Mbak Keyla'. This product exhibits extreme sales volatility, with frequent sharp spikes and sudden drops. The model's predictions in seeking average trends failed due to these drastic and almost random daily changes. This resulted in high MAPE and low overall accuracy.

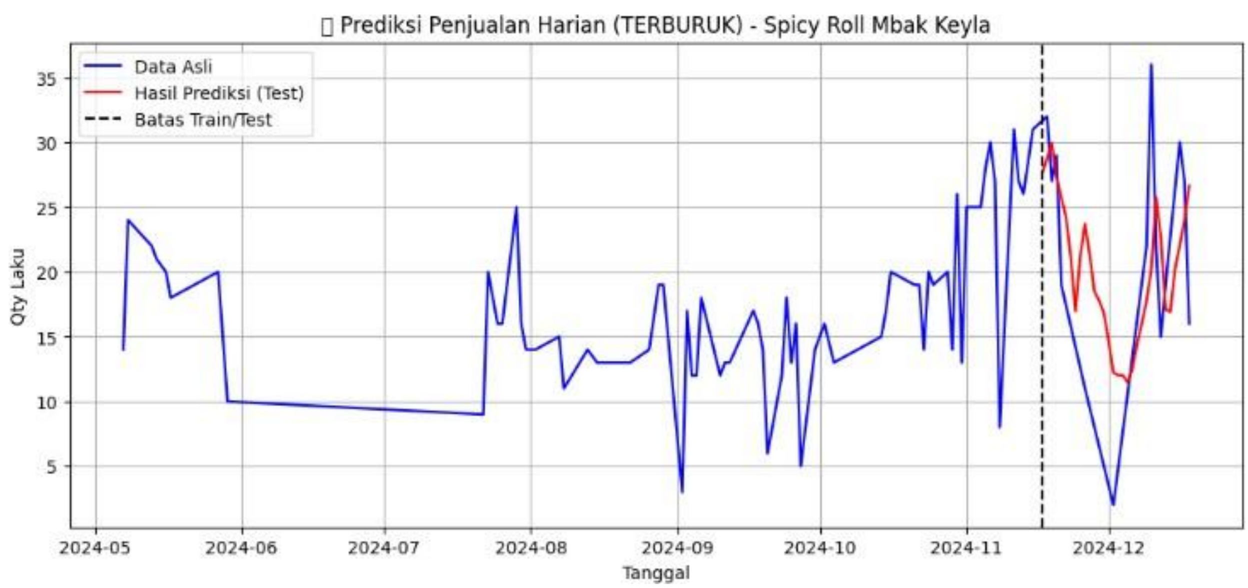

Fig. 3 Low-Accuracy Prediction Figure

These findings reinforce the argument that the LSTM-MLP hybrid approach is capable of providing reliable predictions for products with consistent sales patterns and that adaptive mechanisms are needed to handle data with extreme volatility history (Luo et al., 2022; Venkiteela, 2025). In the context of implementation in cooperatives, this model can be integrated into an automated procurement system with the addition of an alert system feature to flag products with low accuracy (Filali et al., 2022; Mera & Ernawati, 2023).

4. Conclusions

A hybrid Long Short-Term Memory (LSTM) model was implemented to predict daily sales of consignment products at the SMAN 1 Malang Teachers' Cooperative. The proposed model architecture uses a stacked LSTM (two layers) combined with a fully connected layer (MLP), trained on 85% of the training data with a window size of 14 days, and optimized using the EarlyStopping callback (patience=25) and ReduceLROnPlateau callback (factor=0.7). It was then evaluated on 15% of the test data, showing that the model achieved strong performance with an average accuracy of 88.19% (MAPE 11.81%) and a Mean Absolute Error (MAE) of 1.29. This confirms that the hybrid LSTM model is an effective solution for sales forecasting in cooperatives.

The main conclusion of this study is that the effectiveness of the model is highly dependent on product data volatility. The model shows very high accuracy (e.g., MAE ≈ 0.0006) for products with consistent patterns and has difficulty predicting products that experience extreme volatility (e.g., MAE > 4.41). Thus, the prediction results can be used as recommendations: automation of procurement for products with stable data and as a decision support tool requiring managerial review for volatile products. For further studies, it is recommended to explore feature engineering with other external variables, use longer historical data, and compare alternative architectures such as GRU or Transformer.

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