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Multivariate Time Series Forecasting on Sales Using Recurrent Neural Network (Case Study: Aqiqah Almeera)

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ABSTRACT
Sales forecasting is a crucial component in business decision-making, particularly in inventory management and marketing strategies. Accurate sales predictions can help companies maintain stock balance, design effective promotions, and minimize the risk of losses. This study examines the application of Multivariate Time Series Forecasting using Recurrent Neural Networks (RNNs) to more accurately predict product sales. By considering multiple variables such as product price, inventory levels, promotional activities, and temporal features, this approach aims to capture complex and interrelated patterns in historical data. RNNs are chosen for their ability to handle sequential data and learn temporal relationships among variables, thereby improving prediction accuracy. This research adopts a quantitative method with a causal-associative approach, utilizing secondary data from the company's sales records over the past two years. The data is analyzed using various preprocessing techniques such as data normalization, feature encoding, and correlation analysis for optimal feature selection before being fed into the RNN model. The model is trained using specific validation techniques to prevent overfitting. Model performance is evaluated using MAE and RMSE metrics to measure prediction accuracy and reliability. The results of this study are expected to produce an accurate and practical sales forecasting system that can be implemented by business practitioners to support more efficient, data-driven, and well-targeted decision-making processes.

Keyword: Forecasting, Sales, Multivariate Time Series, Recurrent Neural Network, SEMMA

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1. INTRODUCTION

Sales represent a key element in the sustainability of a business, especially for trading companies that rely heavily on sales as their main source of revenue. In an increasingly competitive market environment, companies are required to manage sales strategically and in a data-driven manner [1]. One essential step that can be implemented is sales forecasting to anticipate market demand and manage inventory more efficiently [2]. Sales forecasting plays a significant role in supporting decision-making processes, particularly in inventory control, logistics planning, and revenue estimation. Time series-based forecasting methods allow companies to identify patterns from historical data to predict future trends with greater accuracy [3]. However, univariate approaches are often insufficient to capture the complexity of today's business conditions, which are influenced by multiple variables such as seasonality, promotions, and other external factors.

The Multivariate Time Series Forecasting approach has emerged as a solution to the limitations of univariate models. By incorporating multiple interrelated input variables, this method is capable of producing more accurate and context-aware predictions [3]. As transactional data becomes increasingly complex, the adoption of this approach is becoming essential for companies seeking to remain competitive through data-driven decision-making. In this context, the Recurrent Neural Network (RNN) is a promising model due to its ability to process sequential data and capture intricate temporal patterns effectively [4]. Several previous studies have explored the application of RNNs, including variants such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), across various time series data scenarios. For example, a study by Bagaskara demonstrated that the use of RNNs in retail sales data improved forecasting accuracy, particularly when combined with proper feature engineering techniques [5]. Another study by Zahara also confirmed the effectiveness of this method in modeling complex and multivariable consumer price index data [6].

However, the application of Multivariate Time Series Forecasting methods based on Recurrent Neural Networks (RNN) in product sales prediction still requires further exploration, particularly regarding their practical effectiveness in improving forecasting accuracy. This study aims to analyze the implementation of this method in modeling multivariate product sales data and to evaluate the performance of RNN models in producing reliable predictions.

As a contribution, this research offers novelty by implementing RNN on actual sales data involving multiple determining variables, thereby providing a concrete illustration of the model's capability in supporting business decision-making. The study also provides empirical insights into the effectiveness of RNN in optimizing inventory management and marketing strategies. It is expected that the findings of this research can serve as a reference for companies in leveraging machine learning approaches to enhance operational efficiency and competitiveness in an increasingly digital business landscape.

2. METHODS

This study aims to develop a predictive model based on multivariate time series data using the Recurrent Neural Network (RNN) algorithm. This method is selected due to its capability to handle sequential data and recognize complex temporal patterns, which is highly relevant for forecasting sales based on historical data. In designing the methodological framework, this study adopts the SEMMA (Sample, Explore, Modify, Model, Assess) approach, a data analysis framework developed by the SAS Institute. SEMMA is widely used in data mining and machine learning practices as it provides a systematic, iterative workflow that emphasizes continuous model performance evaluation [7].

Each stage in the SEMMA approach serves a complementary function, beginning with data sampling, exploration of data characteristics, feature transformation, predictive model building, and ending with the final stage of model performance assessment. These stages enable the model development process to be carried out in a structured and accountable manner, allowing the final outcomes to be objectively measured using relevant evaluation metrics. A detailed explanation of each phase in the SEMMA approach is presented as follows:

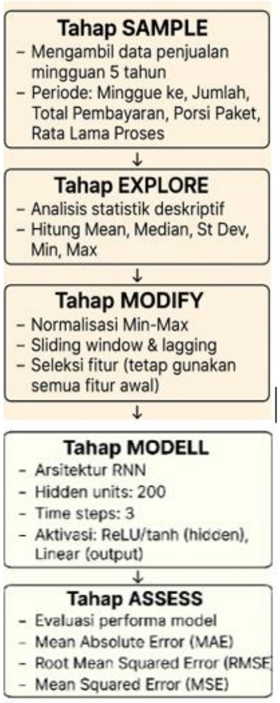

Figure 1. SEMMA Method Flowchart

2.1 Data Collection (Sample)

The Sample stage is the initial step in the SEMMA methodology, where the main focus is data collection and preparation. This stage aims to ensure that the data used meets the requirements for statistical analysis and can be utilized in machine learning models. The quality of data at this stage greatly influences the model's performance in subsequent phases, thus the process is carried out carefully and systematically. The following table presents the key variables used in this study:

Table 1. Dataset Variable Description

Variable Name	Data Type	Description
Month to	Numerik	Indicates the monthly time sequence during the observation period
Amount	Numerik	Indicates the number of heads sold in the corresponding moonth
Total Payment	Numerik	Total transaction value received during the month (in Rupiah)
Package Portion	Numerik	Number of ready-to-eat meal portions produced and delivered
Average Processing Time	Numerik	Average time from order to delivery (in days)

The table above presents the five main variables that serve as inputs for the predictive model. These variables were selected due to their direct relevance to the company’s weekly sales and operational activities. The structuring of data based on the “month number” provides a chronological time framework that is essential for time series analysis.

2.2 Data Exploration (Explore)

The Explore stage aims to gain a deeper understanding of the structure, distribution, and patterns within the collected data. An exploratory approach is applied using descriptive statistics to identify the range, mean, standard deviation, and the potential presence of anomalies such as outliers or irregular patterns. This step is crucial, as basic statistical characteristics provide an initial overview of the stability and consistency of the data to be used in the modeling process.

2.3 Data Modification (Modify)

After gaining an initial understanding of the data, the next step is to prepare the data for the modeling process. This stage involves several technical procedures to clean, align, and transform the data to fit the architecture of the Recurrent Neural Network. The main steps carried out in this phase include:

1. Data Normalization
   Min-Max normalization is used to rescale all features to values between 0 and 1. This is important because RNNs are highly sensitive to numerical scales. Without normalization, features with larger scales (e.g., Total Payment) may dominate the learning process, leading to bias and reduced model performance.
2. Time Series Transformation
   To convert the data into a format compatible with the RNN input structure, sliding window and lagging techniques are applied. The sliding window is implemented with a parameter of *n_steps = 3*, meaning that each input sample consists of three weeks of historical data used to predict the fourth week. Meanwhile, the lagging process helps establish temporal dependencies by creating features based on previous values (e.g., lag-1, lag-2, and so on).
3. Feature Selection
   In this study, all available features were utilized during the model training process. This decision was made because all four features have high relevance to the target variable (*Jumlah*) and contribute to improving prediction accuracy. Using all features allows the model to capture complex multivariate relationships among variables, thereby enhancing its generalization capability and understanding of historical patterns in the weekly sales data.

2.4 Model Development (Model)

This stage represents the core of the SEMMA process, where the predictive model is built using the Recurrent Neural Network (RNN) algorithm. RNN is selected due to its ability to process sequential or time series data with temporal dependencies. Unlike feedforward neural networks, RNNs have a looped structure that allows information from previous time steps to be retained and utilized in predicting future values. This characteristic makes RNNs particularly well-suited for forecasting tasks, including weekly sales prediction based on multivariate historical data [8].

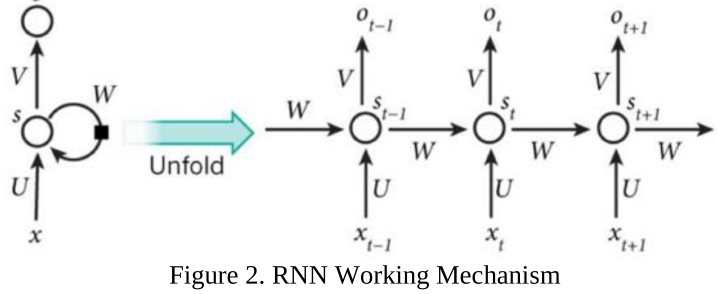

Figure 2. RNN Working Mechanism

RNN performs an unfolding process at each time step, where the output from the previous step influences the processing of the next step through weight parameters (U, V, W). This mechanism enables the model to recognize recurring patterns, seasonal trends, or fluctuations in weekly sales data [9]. After selecting the algorithm and understanding its architecture, the next step is to implement the model in the training and testing process using the prepared data.

1. Data Splitting
   The dataset is divided into two parts: 80% for training and 20% for testing. This strategy is employed to evaluate the model's generalization ability on unseen data and to prevent overfitting.
2. Model Training
   The model was trained for 200 epochs with a batch size of 8, using the Adam optimizer (learning rate of 0.001) and the Mean Squared Error (MSE) loss function. Two callbacks, EarlyStopping and ReduceLROnPlateau, were employed to automatically stop training if validation performance stagnated, and to dynamically adjust the learning rate to accelerate convergence.
3. Model Architecture
   The model was built using Keras' Sequential API, consisting of six main layers:
   a. SimpleRNN with 64 units and return_sequences=True: used to capture data sequences over three time steps.
   b. Dropout (0.2): used to prevent overfitting by randomly deactivating 20% of the units during training.
   c. SimpleRNN with 32 units: used to deepen sequence processing with lighter computational complexity.
   d. Dropout (0.2): used to maintain the model's generalization ability.
   e. Dense (32 units, ReLU activation): used to enhance non-linearity in the feature representation process.
   f. Dense (4 output units): used to generate predictions for the four target variables in a multivariate manner.

   This architecture is designed to capture temporal dependencies across time steps and provide simultaneous predictions for the variables: sales quantity, package portions, total payment, and average processing time.

2.5 Model Evaluation (Assess)

Model evaluation aims to assess how closely the predictions align with actual values and to identify weaknesses that need to be addressed in future development iterations. In time series forecasting, error measurement plays a critical role, as it serves as a foundation for model refinement and algorithm selection. Several metrics were used in this study to evaluate model performance, including Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE). These three metrics are commonly used in predictive regression evaluations as they provide a comprehensive overview of the deviation between predicted and actual values. The smaller the values of these metrics, the more accurate the model's predictions [10].

1. *Mean Absolute Error* (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - x|$$

Description:

n : Number of data points
x_i : Predicted value
x : Actual value

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2. *Mean Absolute Percentage Error* (MAPE)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_i - \hat{x}_i}{\hat{x}_i}\right|$$

Description:

n : Number of data points

x_i : Predicted value

x : Actual value

3. *Root Mean Squared Error* (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)}$$

Description:

n : Number of data points

x_i : Predicted value

3. RESULTS AND DISCUSSION

3.1 Results of Data Collection & Preprocessing

The initial stage of this research process began with the collection of historical sales data obtained from the company's internal archives. The data reflects actual sales activities from three product categories: sheep, goat, and a combination of both. Observations were conducted on a monthly basis, with each data row representing one week of transactions. This structure makes the dataset well-suited for time series analysis, particularly in identifying seasonal patterns and short-term trends.

1. Goat Dataset

Table 1. Normalized Goat Sales Dataset

Ammount	Package Portion	Total Payment	Average Processing Time	Month to
0.461538	0.305263	0.301258	0.234501	1
0.230769	0.136842	0.200633	1.000000	2
0.230769	0.205263	0.182113	0.730458	3
0.230769	0.157895	0.148931	0.427224	4
0.153846	0.178947	0.129640	0.787062	5

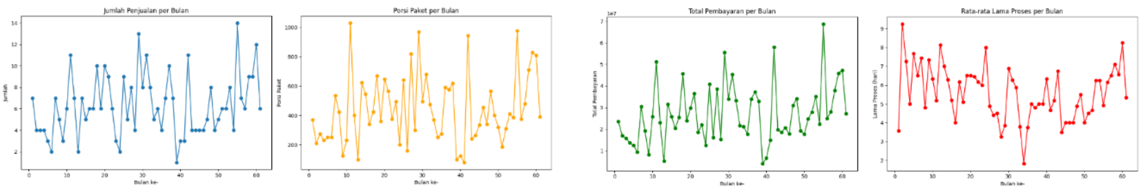

Figure 1. Kambing Sales Distribution Chart

The sheep sales dataset generally exhibits a relatively stable pattern. Monthly sales figures show slight fluctuations, while package portions and total payments remain within a moderate range without significant spikes. The distribution chart indicates transactional stability over time. The average processing time is also fairly consistent, reflecting well-maintained operational performance.

2. Sheep Dataset

Tabel 2. Normalized Domba Sales Dataset

Ammount	Package Portion	Total Payment	Average Processing Time	Month to
0.095238	0.171703	0.113491	0.088679	1
0.142857	0.068681	0.060912	1.000000	2
0.047619	0.061813	0.113262	0.339623	3
0.000000	0.000000	0.000000	0.528302	4

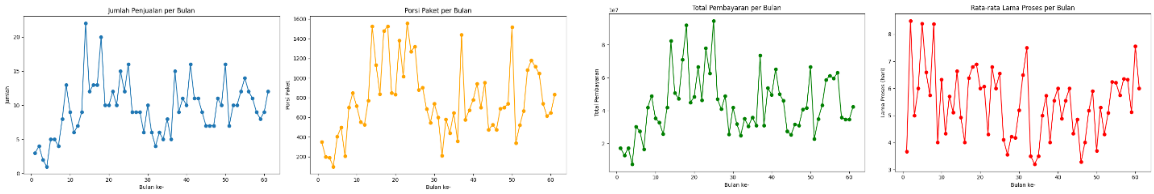

Figure 2. Domba Sales Distribution Chart

The goat sales dataset displays greater variation. Monthly sales figures tend to fluctuate and can exceed 20 animals. Package portions are highly diverse, even surpassing 2,000 units in certain months. Total payments are also significantly higher compared to sheep, indicating a larger transaction scale. Nevertheless, the average processing time remains stable, suggesting effective operational management despite fluctuating demand.

3. Combined Dataset

Table 3. Normalized CombinedSales Dataset

Ammount	Package Portion	Total Payment	Average Processing Time	Month to
0.20	0.184397	0.152801	0.178849	1
0.12	0.037825	0.066940	1.000000	2
0.04	0.063830	0.092904	0.629860	3
0.00	0.000000	0.000000	0.427683	4
0.12	0.153664	0.166383	0.881804	5

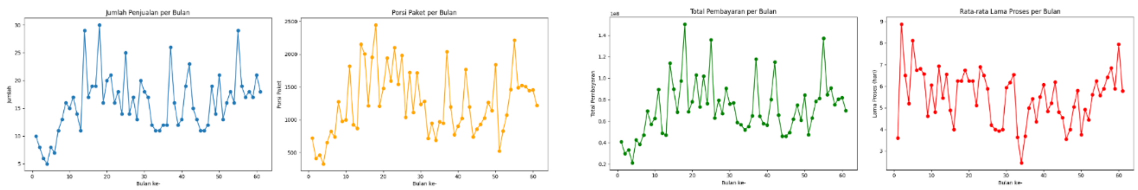

Figure 3. Combined Sales Distribution Chart

Meanwhile, the combined goat and sheep dataset represents the overall sales activity. The values fall between those of the previous two datasets, in terms of sales quantity, package portions, and total payments. Fluctuations are still present, but the distribution is more moderate. The average processing time shows similar stability, despite the increased transaction load resulting from the combination of the two products.

3.2 RNN Model Development

At this stage, the predictive model was built using a Recurrent Neural Network (RNN) architecture, which is known to be effective in processing time series data. The preprocessed dataset was divided into two parts: 80% for training and 20% for testing. To enrich pattern variation, data augmentation was performed using week-to-week interpolation, allowing the model to learn from a greater number of historical data combinations.

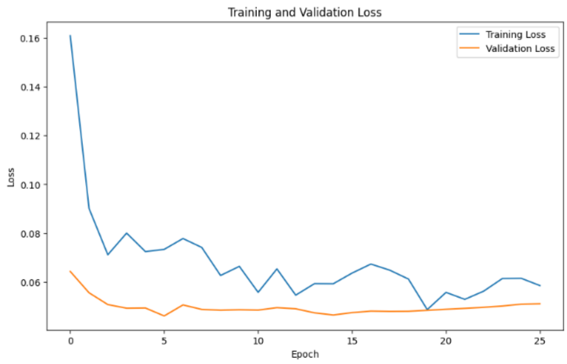

Figure 4. Training and Validation Loss Results

The training graph results indicate a steady decrease in both training loss and validation loss, with no signs of overfitting. This suggests that the model is able to learn effectively from the training data while maintaining generalization to unseen data. The chosen architecture and configuration have proven to be effective in building an accurate and reliable predictive model for the multivariate time series case of goat and sheep sales.

3.3 Model Performance Evaluation

Model evaluation was conducted to assess the accuracy of predictions on the goat, sheep, and combined sales datasets. Three primary metrics were used: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The evaluation was carried out on both the training and testing datasets to assess the model's generalization capability.

1. Training Results

Table 5. Model Performance Evaluation Results on Training Data

Variable	**Sheep**			**Goat**			**Total**		
	MAE	**RMSE**	**MAPE**	**MAE**	**RMSE**	**MAPE**	**MAE**	**RMSE**	**MAE**
Amount	1.37	1.71	13.96%	0.67	0.91	5.16%	0.96	1.33	8.34%
Package Portion	1.46	1.93	15.97%	0.90	1.18	6.57%	1.15	1.43	10.96%
Total Payment	1.31	1.65	13.60%	0.78	1.06	5.80%	1.10	1.38	9.20%
Average Processing Time	1.13	1.42	9.39%	1.21	1.42	10.07%	0.97	1.18	11.18%

On the training data, the model demonstrated fairly good performance, particularly on the goat dataset. For example, in the "Quantity" variable, the MAPE for goats was only 5.16%, significantly lower than that for sheep (13.96%). This indicates that goat sales patterns were easier for the model to learn. Meanwhile, for the overall (combined) dataset, the MAPE remained relatively low. For instance, the "Total Payment" variable recorded a MAPE of only 9.20%, indicating that the model was reasonably capable of accommodating the complexity of both product types simultaneously. The MAE and RMSE values also reflected relatively small errors, suggesting that the model was sufficiently accurate in generating predictions during the training phase.

2. Testing Results

Table 6. Model Performance Evaluation Results on Testing Data

Variable	Sheep			Goat			Total		
	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE
Amount	1.32	1.87	11.85%	0.84	0.96	6.21%	0.79	0.97	6.85%
Package Portion	1.37	1.73	18.87%	0.90	1.23	7.00%	1.05	1.15	10.04%
Total Payment	1.18	1.56	13.50%	0.91	1.02	7.89%	0.59	0.87	7.37%
Average Processing Time	1.00	1.10	8.10%	0.86	0.96	8.46%	0.85	0.99	8.10%

On the testing data, the model maintained stable performance. This is evident from the MAE, RMSE, and MAPE values, which did not differ significantly from those in the training phase. For instance, the "Quantity" variable in the overall dataset recorded a MAPE of 6.85%, indicating good generalization. The goat dataset once again exhibited the best performance, with all variables achieving MAPE values below 8%. Notably, the "Package Portion" variable had a MAPE of only 7.00%, demonstrating the model's consistency in predicting goat sales patterns. Meanwhile, the "Average Processing Time" variable across all three datasets yielded MAPE values ranging from 8% to 11%, which is considered reasonably good given that this process can be influenced by random operational factors.

3.4 Prediction Results

After the model was trained and evaluated, predictions were carried out for the next 12 months on three data groups: sheep, goats, and the combined dataset. These forecasts encompass four key variables—Number of Orders, Package Portion, Total Payment, and Average Processing Time—serving as a basis to support future business planning and operational strategy.

Table 7. Prediction Results for Sheep Dataset

Month	Ammount	Package Portion	Total Payment	Average Processing Time
62	7.34	429.23	33,216,192	5.79
63	6.98	409.43	33,616,388	4.59
64	6.11	426.93	28,083,316	5.15
65	5.78	422.93	27,676,870	4.58
66	5.59	409.00	25,391,022	4.85
67	5.38	396.18	26,040,996	4.56
68	5.45	389.17	25,476,716	4.68
69	5.28	384.61	25,520,184	4.52
70	5.32	385.63	25,027,828	4.59
71	5.20	383.01	24,892,508	4.51
72	5.21	382.64	24,625,664	4.55

The sheep dataset shows a consistent downward trend in the number of orders and transaction values. From month 62 to 72, orders declined from approximately 7.34 to 5.21, accompanied by a decrease in package portions and total payments. Nevertheless, the average processing time remained stable between 4.5 and 5.8 days, indicating that operational efficiency was maintained despite the reduction in transaction volume.

Table 8. Prediction Results for Goat Dataset

Month	Ammount	Package Portion	Total Payment	Average Processing Time
62	9.25	577.22	44,539,792.0	5.04
63	9.86	770.50	40,208,552.0	5.44
64	9.05	836.94	41,416,624.0	5.44
65	9.71	736.75	41,379,988.0	5.06
66	9.83	749.50	41,263,476.0	5.26
67	9.99	780.83	40,623,040.0	5.34
68	9.94	756.22	41,210,392.0	5.18
69	9.99	756.95	41,495,592.0	5.23
70	9.91	778.89	41,370,256.0	5.26
71	9.94	766.90	41,342,416.0	5.22
72	9.99	765.35	41,414,960.0	5.22

In contrast, the goat dataset exhibits a stable trend, with signs of gradual growth. The number of orders steadily increases to nearly 10 per month, with package portions consistently high at over 750 units. Total payments also remain stable within the range of IDR 40–44 million. The processing time stays between 5 and 5.4 days. These results indicate strong growth potential for the goat service.

Table 9. Prediction Results for Combined Dataset

Month	Ammount	Package Portion	Total Payment	Average Processing Time
62	16.80	1543.99	97,502,416	5.78
63	18.18	1349.10	82,301,160	5.80
64	17.33	1540.93	93,062,296	5.45
65	18.15	1548.89	87,901,576	5.81
66	17.76	1575.22	91,843,032	5.60
67	18.05	1570.88	90,536,416	5.74
68	18.03	1563.82	91,664,320	5.65
69	18.13	1571.11	91,458,296	5.70
70	18.13	1569.65	91,740,240	5.67
71	18.15	1574.78	91,872,408	5.69
72	18.16	1573.45	91,915,424	5.68

In the combined dataset, the forecast reflects operational stability and strong demand. The number of orders increases from 16.80 to 18.16, with package portions remaining high at over 1,500 units and total payments ranging between IDR 91–97 million. Processing time also remains consistent, around 5.6–5.8 days. This indicates that overall, the system is capable of maintaining high performance even at a large transaction scale.

CONCLUSION

This study successfully implemented a Multivariate Time Series Forecasting approach using a Simple RNN architecture to predict the sales of goats, sheep, and their combined data. The model demonstrated reasonably good performance, particularly for the combined dataset, which achieved MAPE values below 20% across all variables. The two-layer RNN architecture (with 64 and 32 units) and a 0.2 dropout rate proved effective in capturing temporal patterns and preventing overfitting, although prediction accuracy on individual datasets varied depending on their characteristics.

The 12-month forecast results indicate stable to increasing trends, especially for goat services and the combined dataset. Order volume and total payment are expected to remain high, while processing duration stays within an efficient range. These findings affirm the potential of the model as a supporting tool for operational planning and strategic decision-making in future business management.

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