

Analysis and Visualization of Kare Kambing Sales Forecasting Using Time Series-Based Forecasting and Machine Learning

Vinka Amelia Surya Putri¹, I Kadek Dwi Nuryana²

^{1,2}*Universitas Negeri Surabaya, Surabaya, Indonesia*

vinka.22061@mhs.unesa.ac.id, dwinuryana@unesa.ac.id

ABSTRACT

The Kare Kambing MSME possesses a substantial amount of historical sales data, yet its utilization as a basis for business decision-making remains suboptimal. Production planning is currently based on estimates, creating a risk of either overproduction or underproduction. This study aims to analyze sales patterns, compare various forecasting methods, and visualize the analysis results via a Business Intelligence dashboard to support business decision-making. The study utilizes historical sales data from the Kare Kambing MSME covering the period from 2020 to February 2026. The research stages include data preprocessing, exploratory data analysis (EDA), forecasting model development, model evaluation, sales forecasting, and dashboard creation using Tableau. The models compared are Moving Average, Exponential Smoothing, ARIMA, Linear Regression, and Random Forest. Model evaluation was conducted using MAE, RMSE, and SMAPE metrics, with data split into 80% for training and 20% for testing. The results indicate fluctuating sales patterns, characterized by day-to-day variations and relatively stable seasonal trends. Based on the evaluation, the Linear Regression model emerged as the best performer, achieving an MAE of 61.93, RMSE of 77.82, and SMAPE of 7.25. This model was subsequently used to forecast sales for the period of March 2026 through December 2027, yielding a total predicted volume of 17,623 portions. Finally, the forecast results were visualized in a Tableau dashboard to facilitate sales monitoring, model evaluation, and the structured formulation of raw material inventory recommendations.

Keyword: Forecasting, Time Series, Linear Regression, Business Intelligence, Tableau, MSMEs

Article Info:

Article history:

Received July 07, 2026

Revised August 07, 2026

Accepted September 14, 2026

Corresponding Author

Vinka Amelia Surya Putri

Universitas Negeri Surabaya, Surabaya, Indonesia

vinka.22061@mhs.unesa.ac.id

1. INTRODUCTION

The evolution of digital transformation drives business organizations to leverage data as a foundation for faster, objective, and measurable decision-making [1], [2]. Transaction data, which previously served merely as operational records, can now be transformed into valuable information through analysis, visualization, and predictive processes [1], [3]. In a business context, a crucial application of data is forecasting—the process of estimating future conditions based on historical patterns to support operational planning and control [4], [5]. Forecasting is widely used to estimate demand, plan inventory, manage production capacity, and minimize the risks of stockouts or overstocking [4], [6], [7].

For MSMEs, forecasting is increasingly vital limited resources mean that errors in production planning can directly impact operational costs and business profitability [6], [7]. Culinary MSMEs—particularly those dealing with fresh products or items with a limited shelf life—require accurate sales estimates to ensure that raw materials, production volumes, and labor are prepared proportionately [6], [8]. In practice, however, many MSMEs still rely on manual estimates and the business owner's experience to determine daily production levels [2], [7]. Such approaches carry the risk of overproduction when demand drops or stock shortages when demand rises [4], [6].

The Kare Kambing MSME is a culinary business with a substantial amount of historical sales data; however, these data have not been utilized optimally to support business decision-making. At present, production planning is still based largely on estimation, which may lead to discrepancies between production volume and actual market demand. In fact, historical sales data can be analyzed to identify demand patterns, evaluate sales performance, and develop forecasting models for future sales. By leveraging these data, the business can make operational decisions related to raw material preparation, production planning, and inventory management in a more systematic and data-driven manner.

Previous studies have shown that sales forecasting can be performed using various approaches, including both statistical methods and machine learning techniques. Statistical methods such as ARIMA and Exponential Smoothing are widely used because they are capable of capturing trend and seasonal patterns in time series data [4], [5]. On the other hand, machine learning approaches such as Random Forest and Linear Regression are also frequently applied to learn relationships among time-related features and generate competitive predictions [9], [10], [11]. Several comparative studies have indicated that no single model consistently outperforms others across all datasets, as model performance is strongly influenced by data characteristics, the length of historical observations, the level of fluctuation, and the presence of seasonal or nonlinear patterns [4], [5], [9]. Therefore, the selection of the best forecasting model should be based on a comparative evaluation of multiple models using consistent performance metrics [5], [9].

In addition to the prediction aspect, forecasting results also need to be presented in a form that is easy for business owners to understand. Business Intelligence (BI) and interactive dashboards play an important role in transforming analytical results into visual information that can support performance monitoring, trend evaluation, and business decision-making [1], [4], [12]. A well-designed dashboard can present sales indicators, demand patterns, model performance, forecasting results, and operational recommendations in a concise and integrated view [3], [12]. For MSMEs, presenting forecasting results through a dashboard can help business owners who do not have a technical background to better understand analytical information and use it in day-to-day decision-making [2], [12].

Based on the background described above, this study aims to analyze the sales patterns of the Kare Kambing MSME, compare the performance of five forecasting models, namely Moving Average, Exponential Smoothing, ARIMA, Linear Regression, and Random Forest, and identify the best-performing model for sales forecasting. In addition, this study seeks to visualize the results of the sales analysis and forecasting in a Business Intelligence dashboard using Tableau. The contribution of this study lies in the integration of historical sales analysis, comparative forecasting methods, and BI dashboard visualization within the context of a culinary MSME. Therefore, the findings are expected not only to identify the most suitable forecasting model, but also to provide actionable information that can support operational planning and business decision-making.

2. METHODS

This study employed a quantitative approach using historical sales data from the Kare Kambing MSME as the research object. The analyzed dataset covered the period from 2020 to February 2026 and included transaction dates, production quantity, quantity sold, unsold stock, and revenue. The research process began with data collection and data cleaning to ensure that the dataset was ready for analysis. The data cleaning stage was carried out to address inconsistencies in data format, ensure attribute completeness, and minimize potential disturbances in the modeling process [4], [5]. After the data had been cleaned, exploratory data analysis (EDA) was conducted to understand the characteristics of sales performance, including sales trends, seasonal patterns, data distribution, differences in sales levels across days, and peak sales hours. EDA is an important stage because the characteristics of historical data can influence both the selection of forecasting methods and the interpretation of forecasting results [4], [9].

In the forecasting stage, this study compared five models, namely Moving Average, Exponential Smoothing, ARIMA, Linear Regression, and Random Forest. The selection of these five models was based on the intention to compare two major forecasting approaches, namely statistical time series methods and machine learning methods for sales prediction [4], [5], [9]. Moving Average was used as a baseline model to capture short-term historical average tendencies [13]. Exponential Smoothing was selected because it assigns greater weight to more recent observations, making it relevant for sales patterns that change gradually [14], [13]. ARIMA was employed because it is one of the most widely used classical methods in time series forecasting and is effective for handling data with autoregressive and differencing structures [5], [10]. Meanwhile, Linear Regression and Random Forest were included to represent machine learning approaches that utilize time-related features extracted from historical sales data [15].

Before modeling, the dataset was divided into 80% training data and 20% testing data. This split was applied so that the models could be trained on the majority of historical data and then evaluated on unseen data, allowing model performance to be assessed more objectively [4], [5]. Model evaluation was conducted using three metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Symmetric Mean Absolute Percentage Error (SMAPE). MAE was used to measure the average absolute difference between actual and predicted values, while RMSE was used to assign a larger penalty to extreme prediction errors [5], [9]. SMAPE was selected because Kare Kambing sales data contained zero-sales values in certain periods, making SMAPE more stable than MAPE for measuring percentage-based forecasting errors under such conditions [5], [9]. The best model was selected based on the consistency of achieving the lowest error values across the three evaluation metrics.

After the best-performing model had been identified, it was used to build the final forecasting model and generate sales forecasts for the period from March 2026 to December 2027. The forecasting results were then translated into recommendations for raw material stock requirements based on the assumed material needs per portion and the raw material conversion factors defined in this study. In the final stage, the results of the historical data analysis, model evaluation, and sales forecasting were visualized in Tableau through a Business Intelligence dashboard. The developed dashboard consisted of a Historical Sales Monitoring Dashboard, a Sales Pattern Analysis Dashboard, a Forecasting Model Evaluation Dashboard, and a Sales Forecast Dashboard. Presenting the results in the form of a dashboard was intended to enable MSME owners to understand analytical information more quickly and to use it directly for monitoring and decision-making purposes [4], [12].

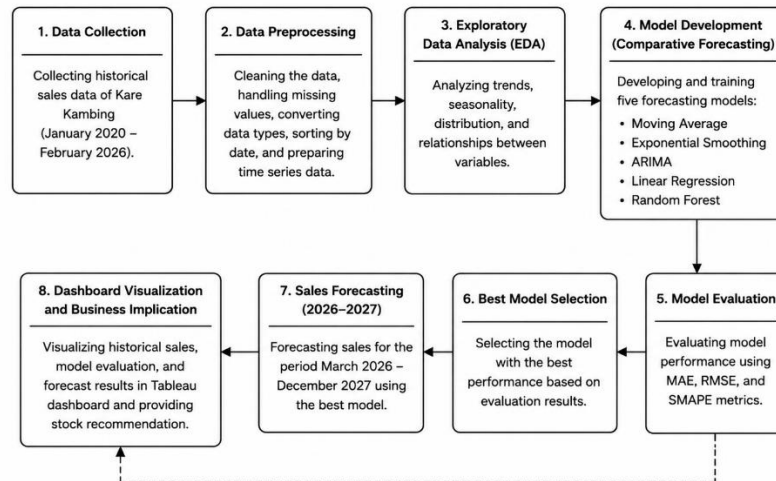


Figure 1. ML Forecasting Stages

3. RESULTS AND DISCUSSION

3.1 Data Collection

This study used primary data obtained directly from the Kare Kambing MSME in the form of historical daily sales data covering the period from January 2020 to February 2026. The data were stored in tabular format and contained daily sales transaction information along with supporting operational variables. In general, the dataset included variables such as date, day, production quantity, quantity sold, unsold stock, revenue, day category, peak hours, and other derived time-related variables used in the analysis and modeling stages.

Table 1. Dataset Variabels

Variable	Description
Date	Transaction date
Day	Day of the transaction
Production Quantity (Portions)	Number of portions produced
Quantity Sold (Portions)	Number of portions sold.
Remaining Stock (Portions)	Number of unsold portions remaining.
Price per Portion	Selling price per portion
Revenue	Total sales revenue
Peak Hour 1	Hour with the highest sales activity
Peak Hour 2	Hour with the second-highest sales activity
Day Category	Category representing the type of day

Daily sales data were selected because they were appropriate for the purpose of this study, which was to analyze time series sales patterns and develop sales forecasting models for future periods. Before being used for modeling, the data underwent a data cleaning process

and feature transformation to ensure that they were suitable for exploratory data analysis and forecasting model comparison. The final dataset used in this study consisted of 2,252 daily records. The variables used in this study are shown in Table 1.

3.2 Data Preprocessing

Data cleaning was conducted as an initial stage to ensure data quality before the dataset was used for analysis and forecasting. This stage aimed to identify and address potential data issues such as missing values, duplicate records, data format inconsistencies, and overall data consistency. The data cleaning process was performed using Python in Google Colab. The following table presents the sales data after the data cleaning process:

	A	B	C	D	E	F	G	H	I	J
	Tanggal	Hari	Jumlah Produksi (Porsi)	Terjual (Porsi)	Sisa (Porsi)	Harga per Porsi	Omset	Jam Ramai 1	Jam Ramai 2	Kategori_Hari
1										
2	01/01/2020	Rabu	36	17	19	15000	255000	11		13 Sepi
3	02/01/2020	Kamis	83	18	64	15000	270000	8		13 Sepi
4	03/01/2020	Jumat	34	28	6	15000	420000	8		13 Normal
5	04/01/2020	Sabtu	72	21	51	15000	315000	8		12 Normal
6	05/01/2020	Minggu	50	13	37	15000	195000	11		13 Sepi
7	06/01/2020	Senin	72	22	47	15000	375000	8		12 Normal
8	07/01/2020	Selasa	30	30	0	15000	450000	8		13 Habis
9	08/01/2020	Rabu	41	41	0	15000	615000	8		13 Habis
10	09/01/2020	Kamis	78	10	68	15000	150000	8		12 Sepi
11	10/01/2020	Jumat	87	5	82	15000	75000	8		17 Sepi
12	11/01/2020	Sabtu	41	24	17	15000	360000	8		13 Normal
13	12/01/2020	Minggu	32	11	21	15000	165000	11		13 Sepi
14	13/01/2020	Senin	91	18	73	15000	270000	8		13 Sepi
15	14/01/2020	Selasa	34	25	9	15000	375000	8		12 Normal
16	15/01/2020	Rabu	96	26	70	15000	390000	8		13 Normal
17	16/01/2020	Kamis	97	30	67	15000	450000	8		12 Normal
18	17/01/2020	Jumat	31	30	1	15000	450000	8		12 Normal
19	18/01/2020	Sabtu	95	37	58	15000	555000	8		17 Normal
20	19/01/2020	Minggu	92	33	59	15000	495000	11		13 Normal
21	20/01/2020	Senin	77	47	30	15000	705000	8		13 Normal
22	21/01/2020	Selasa	53	22	31	15000	330000	8		13 Normal
23	22/01/2020	Rabu	92	25	67	15000	375000	8		13 Normal
24	23/01/2020	Kamis	72	32	40	15000	480000	8		13 Normal
25	24/01/2020	Jumat	39	32	7	15000	480000	8		12 Normal

Figure 2. Data Cleaning

3.3 Analysis of Sales Patterns

The exploratory data analysis results indicate that Kare Kambing sales exhibited a fluctuating pattern over the observation period. As shown in the annual sales trend, the average sales level increased from 2020 to 2021, remained relatively high in 2022, and then declined noticeably in 2023. After that, sales tended to stabilize during 2024 and 2025, before decreasing again in early 2026. This pattern suggests that customer demand was not constant over time, and therefore production decisions should not rely solely on rough average sales figures, but should also consider historical sales behavior in greater detail [4], [6].

The observed fluctuations also indicate that the level of demand changed across periods, which may reflect shifts in customer purchasing behavior and operational conditions. Such findings are consistent with the sales forecasting literature, which emphasizes the importance of identifying historical trends and demand patterns before developing predictive models [4], [5].

In addition to the overall trend, the daily sales analysis shows that sales levels on weekdays tended to differ from those on Sundays. In this study, the Normal day category was the most dominant compared with the Low and Sold-Out categories. This condition indicates that most sales activities occurred at a relatively stable level of demand, although there were still certain days with low demand as well as days when stock was sold out. For MSMEs, such information is important because it can be used to manage daily production capacity and adjust the amount of raw materials that need to be prepared [6], [7].

Further analysis of peak hours shows that the busiest sales periods most frequently occurred around 08:00 a.m. and 12:00–1:00 p.m. This pattern indicates the presence of two recurring peaks in sales activity, which can be utilized by the business owner to adjust raw material preparation schedules, allocate labor more effectively, and ensure service readiness during those periods. In the operational context of a culinary MSME, information regarding peak hours has practical value because it helps the business allocate resources at the times they are most needed [6], [9].

Overall, the EDA results demonstrate that Kare Kambing's historical sales data are not only useful for documentation purposes, but can also be utilized to understand customer demand characteristics and the operational conditions of the business. Information regarding sales trends, day categories, and peak hours provides an important foundation for the forecasting process, since the predictive models developed should be based on a clear understanding of historical data behavior [4], [5].

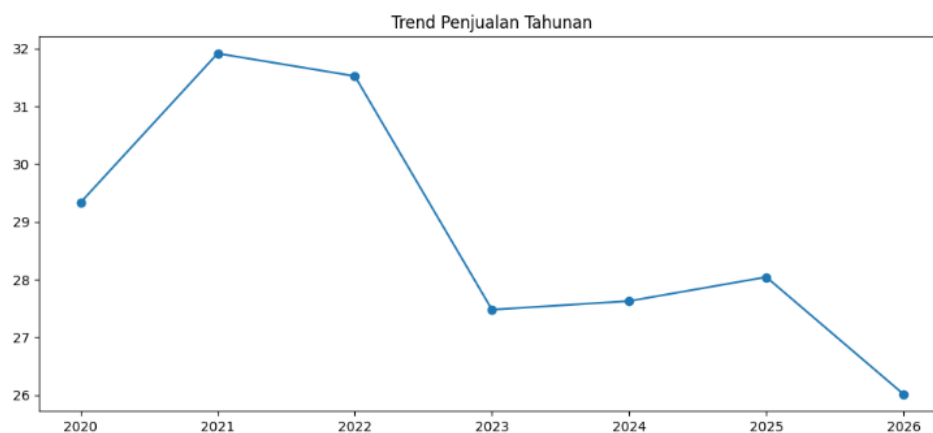


Figure 3. Sales Trends

The time series decomposition results indicate that Kare Kambing sales consist of trend, seasonal, and residual components. The **seasonal** component fluctuates repeatedly around the central value, suggesting the presence of a recurring seasonal pattern, although its effect is not highly dominant. The **trend** component shows an increase in sales from 2020 to early 2022, followed by a decline during 2022–2023, and then a relatively stable pattern with a slight increase until 2025. Meanwhile, the **residual** component is distributed randomly around zero, indicating that most of the sales pattern has been captured by the trend and seasonal components, while the remaining variation may be influenced by other factors outside the model. Overall, these results suggest that Kare Kambing sales exhibit a relatively stable and recurring seasonal pattern, which is important for improving forecasting accuracy.

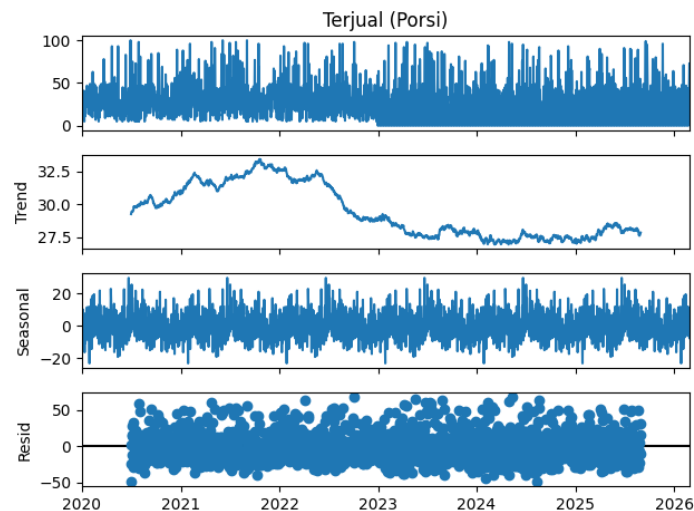


Figure 4. Seasonality Chart

Correlation analysis was conducted using the Pearson correlation coefficient to examine relationships among variables in the dataset. The results show that Quantity Sold (Portions) and Revenue have a perfect positive correlation ($r = 1.00$), indicating that higher sales directly increase revenue, which is reasonable because revenue is derived from the number of portions sold. Production Quantity (Portions) has a moderate positive correlation with Quantity Sold and Revenue ($r = 0.41$), suggesting that higher production tends to be associated with higher sales performance. In contrast, Remaining Stock (Portions) shows a moderate negative correlation with Quantity Sold and Revenue ($r = -0.38$), indicating that greater sales are associated with lower unsold stock. Meanwhile, the time-related variables Day Index and Month have relatively weak correlations with the other variables, ranging from -0.16 to 0.09. Overall, these findings suggest that operational variables, particularly production, sales, remaining stock, and revenue, have stronger relationships than the time-related variables, making them more relevant for forecasting and stock planning.

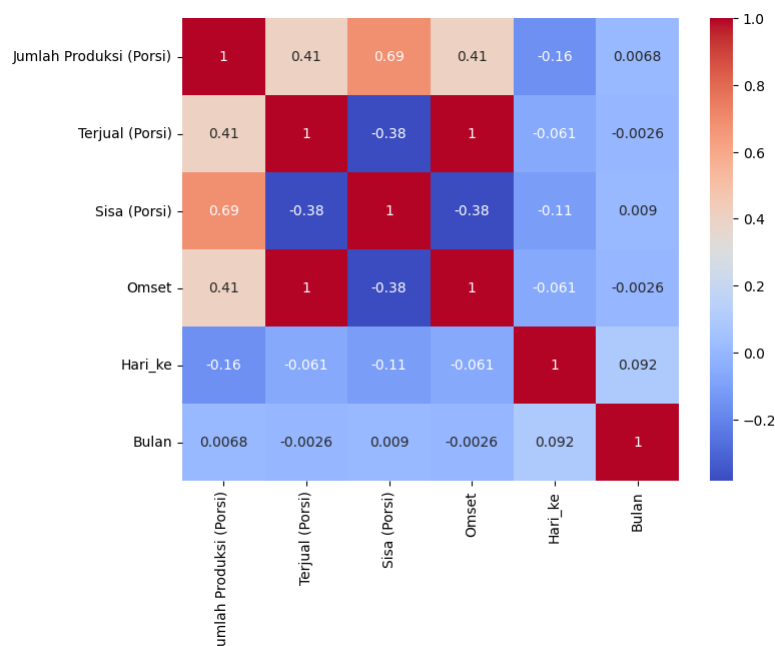


Figure 5. Variable Correlation Heatmap

3.4 Data Split 80:20

The sales dataset was divided into training and testing sets using an 80:20 ratio. Of the total 74 monthly observations, 59 were used as training data and 15 as testing data. The training set covered the period from January 2020 to November 2024, while the testing set covered December 2024 to February 2026. This split was applied so that the forecasting models could be trained on historical data and then evaluated on previously unseen data to assess their predictive performance.

3.5 Training and Evaluation

At the forecasting stage, this study compared five models: Moving Average, Exponential Smoothing, ARIMA, Linear Regression, and Random Forest. These models were selected to represent two different forecasting approaches, namely statistical time series methods and machine learning methods [4], [5], [9]. Comparing multiple models is necessary because no single model consistently performs best across all datasets, as forecasting performance is influenced by data patterns, the length of historical observations, and the relationships among variables [4], [5].

Based on the evaluation results, Linear Regression was identified as the best-performing model in this study. It achieved the lowest error values among all models, with a MAE of 61.93428305, RMSE of 77.82004986, and SMAPE of 7.252379921. These results indicate that the predictions generated by Linear Regression were the closest to the actual Kare Kambing sales values in the testing data. Therefore, this model was selected as the final model for forecasting future sales.

The results suggest that Kare Kambing sales patterns can still be captured effectively by a relatively simple model such as Linear Regression. This indicates that the sales data exhibit a fairly stable pattern and that the underlying relationships can be represented adequately through the time-related features used in the model. Under such conditions, a linear model may provide more accurate predictions than more complex alternatives. This finding is consistent with previous studies showing that Linear Regression remains relevant for sales or demand forecasting when the data exhibit a relatively clear trend and limited complexity [9], [4].

On the other hand, Random Forest and ARIMA also demonstrated reasonably good performance, but they did not outperform Linear Regression on this dataset. Random Forest is generally more suitable for capturing more complex nonlinear patterns, while ARIMA is more effective for time series data with strong autocorrelation structures [5], [8]. However, in this study, the structure of Kare Kambing sales data appears to be more compatible with a linear time-based modeling approach, which explains why Linear Regression produced the best evaluation results.

Table 2. Model Evaluation Results

Model	MAE	RMSE	SMAPE
Linear Regression	61.93428305	77.82004986	7.252379921
Random Forest	62.32205394	81.73472691	7.29807831
Exponential Smoothing	66.0361369	88.66311261	7.733327035
ARIMA	66.65668123	88.5292741	7.810144232
Moving Average	81.66666667	95.32156104	9.56379383

3.6 Analysis of Sales Forecast Patterns

After the best-performing model had been identified, the next step was to generate sales forecasts using the Linear Regression model. This model was applied to predict Kare Kambing sales for the period from March 2026 to December 2027. The forecasting results indicate that the total predicted sales during this period reached 17,623 portions, with an average of approximately 801 portions per month. The highest forecast value was around 862 portions, while the lowest forecast value was approximately 743 portions.

The forecasting results suggest that Kare Kambing sales in the upcoming period are likely to remain within a relatively stable range, although monthly fluctuations are still present. These fluctuations may be influenced by historical sales patterns, variations in the number of active selling days, and differences in consumer demand across periods. By providing these projections, the forecasting model offers the MSME owner a more measurable estimate of future sales levels.

From an operational perspective, the forecast results can serve as a basis for production planning and raw material procurement. When the forecast indicates an increase in sales, the business owner can prepare a larger stock of raw materials to anticipate higher demand. Conversely, when the forecast suggests a decline, production volume can be adjusted to reduce the risk of overstock and unnecessary waste. In this way, forecasting not only generates numerical predictions, but also functions as a practical decision-support tool for more rational and data-driven business planning [1], [6].

In addition to providing a quantitative view of future sales, the forecasting results also demonstrate that the use of historical sales data can improve business planning quality. If production decisions were previously based mainly on estimation or intuition, forecasting enables those decisions to be supported by more objective analytical results. This is particularly important for MSMEs, as errors in demand estimation may directly affect operational efficiency, product availability, and potential business revenue [4], [6].

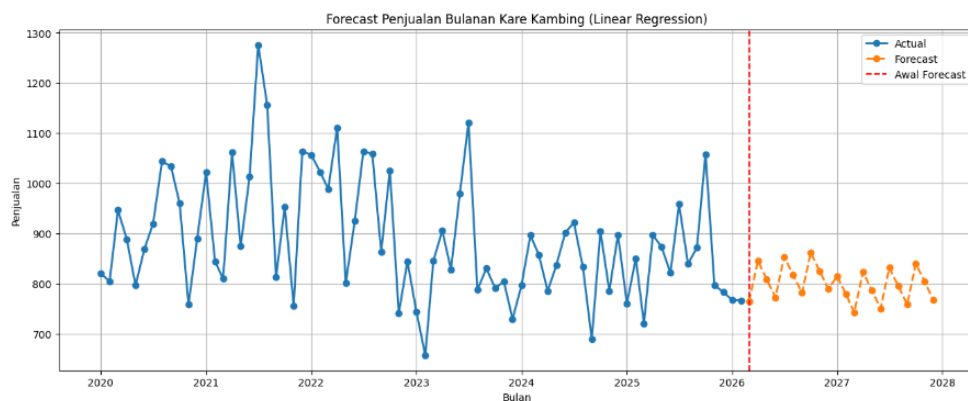


Figure 6. Sales Forecasting Result

3.7 Implementation of Tableau Business Intelligence Dashboard

The results of the analysis and forecasting in this study were then visualized through a Business Intelligence dashboard developed using Tableau. The dashboard was designed to present sales information in a more interactive, concise, and user-friendly manner for the MSME owner. The implementation of the dashboard represents an important component of

this study, as forecasting results should not only be accurate in numerical terms, but also be presented visually in a way that supports practical and informed decision-making [8].

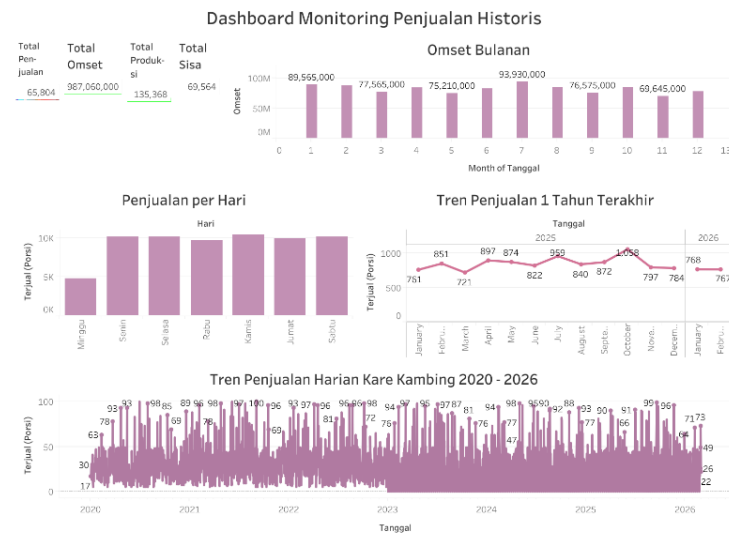


Figure 7. Historical Sales Monitoring Dashboard

The historical sales monitoring dashboard was designed to present a visual summary of Kare Kambing sales to support analysis and business decision-making. At the top of the dashboard, several key indicators are displayed, including total sales of 65,804 portions, total revenue of IDR 387,060,000, total production of 135,368 portions, and remaining stock of 69,564 portions, providing an overview of overall sales performance during the observation period.

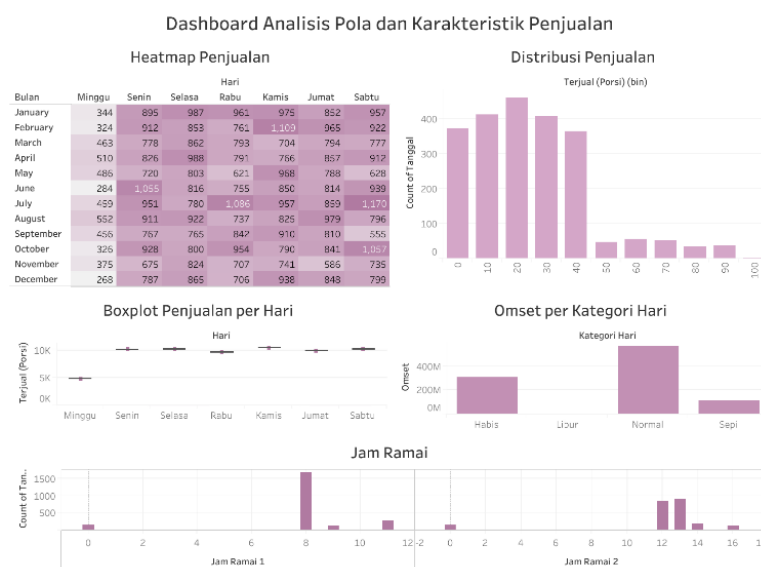


Figure 8. Sales Pattern Analysis Dashboard

In addition, the dashboard presents monthly revenue through a bar chart, sales by day of the week to highlight daily sales differences, and a one-year sales trend chart to monitor recent monthly changes. It also includes a daily sales trend visualization for 2020–2026, which provides a more detailed view of long-term sales patterns, fluctuations in demand, and periods of increasing or declining sales. Overall, this dashboard serves as a visual tool for

understanding historical sales performance and supporting more informed business decisions.

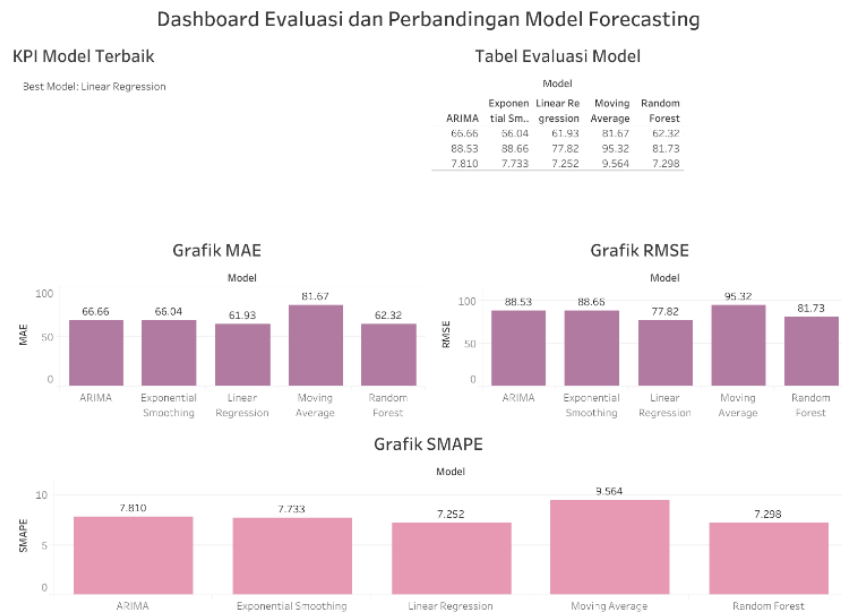


Figure 9. Forecasting Model Evaluation Dashboard

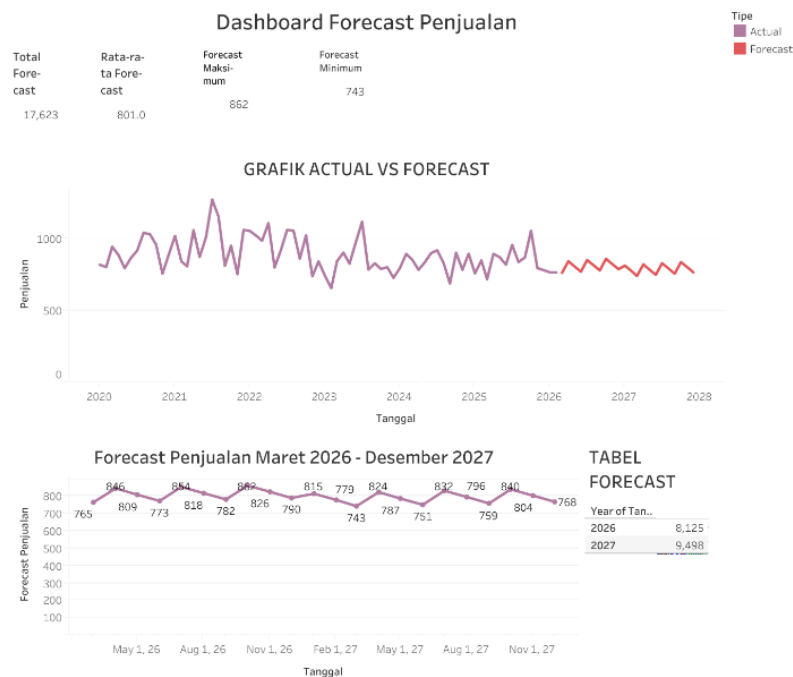


Figure 10. Sales Pattern Forecast Dashboard

The Sales Forecast Dashboard was developed to visualize Kare Kambing sales projections for the period March 2026 to December 2027 using the best-performing forecasting model, namely Linear Regression. The dashboard presents forecast results through key performance indicators (KPIs), an Actual vs Forecast chart, a monthly forecast trend, and a yearly forecast summary table.

The KPI section shows that the total forecast for the prediction period is 17,623 portions, with an average of 801 portions per month. The highest forecast value is 862 portions, while the lowest is 743 portions, indicating that predicted sales remain within a relatively stable range. The Actual vs Forecast chart compares historical sales with predicted values and shows that sales during 2026–2027 are expected to fluctuate moderately while following a stable overall pattern.

In addition, the yearly forecast summary indicates that total projected sales are 8,125 portions in 2026 and 9,498 portions in 2027, suggesting a slight increase in sales in 2027. Overall, this dashboard provides a concise and informative overview of future sales projections, which can support production planning, stock management, and business decision-making.

Through that dashboard, business owners can monitor their company's performance in a faster and more efficient way without having to manually read through raw data. Information such as sales trends, model performance comparisons, and forecast results can be viewed all at once on an integrated display. This makes the dashboard an effective tool for turning the results of data analysis into operational information that is easier to use when making decisions [8], [10].

CONCLUSION

The Sales Forecast Dashboard successfully visualized Kare Kambing sales projections for the period from March 2026 to December 2027 based on the best-performing forecasting model, namely Linear Regression. The dashboard results indicate that projected sales remain relatively stable, with moderate monthly fluctuations and a slight increase in total projected sales in 2027 compared with 2026. These findings demonstrate that integrating forecasting results into a Business Intelligence dashboard can effectively support the interpretation of future sales patterns and provide practical insights for production planning, stock management, and business decision-making in culinary MSMEs.

ACKNOWLEDGEMENTS

The author would like to thank UMKM Kare Kambing Pak XX for the support, operational data, and research collaboration provided during this study. The author also expresses gratitude to Universitas Negeri Surabaya, especially the Information Systems Study Program, for the academic support and facilities that contributed to the completion of this research. Appreciation is also addressed to the research supervisor for the guidance, feedback, and motivation throughout the research and article preparation process.

REFERENCES

- [1] E. Spiliotis, “Time series forecasting with statistical , machine learning and deep learning methods : Past , present and future,” in *Palgrave Advances in the Economics of Innovation and Technology*, A. N. Link, Ed., pp. 1–21. doi: 10.1007/978-3-031-35879-1_3.
- [2] R. Godahewa, C. Bergmeir, G. I. Webb, and P. Montero-manso, “An Accurate and Fully-Automated Ensemble Model for Weekly Time Series Forecasting,” vol. 2, pp. 1–36, 2023.

- [3] M. A. S. Hasibuan, Z. Indra, F. A. Lubis, and N. Farezi, "Student Enrollment Forecasting System Using ARIMA Time Series and Linear Regression Methods," *J. Ilm. Sist. Inf.*, vol. 4, no. 1, pp. 973–983, 2025, doi: <https://doi.org/10.51903/n95g4460>.
- [4] T. Gärtner, C. Lippert, and S. Konigorski, "AUTOMATED DEMAND FORECASTING IN SMALL TO MEDIUM-SIZED ENTERPRISES," vol. 1, pp. 1–14, 2024.
- [5] S. S. Yadav, "Sales Forecasting for Small Medium Enterprises Using Machine Learning," 2025, [Online]. Available: <https://norma.ncirl.ie/id/eprint/7291>
- [6] M. R. Hasan, M. A. Kabir, R. A. Shuvro, and P. Das, "A Comparative Study on Forecasting of Retail Sales Related Works," pp. 1–14, 2020.
- [7] S. A. Agomah and I. K. Ukabuiro, "Intelligent Sales Forecasting Technique Application," *Eur. J. Theor. Appl. Sci.*, vol. 1, no. 6, pp. 641–653, 2023, doi: 10.59324/ejtas.2023.1(6).64.
- [8] A. Waghmare, R. Thakur, and P. R. Khatri, "From Data to Decisions : Using Tableau to Visualize Sales Success," *Int. J. Multidiscip. Res.*, vol. 7, no. 2, pp. 1–20, 2025, doi: <https://doi.org/10.36948/ijfmr.2025.v07i02.43232>.
- [9] N. L. S. April Yanti, N. W. J. Kusuma Dewi, I. G. M. Yudi Antara, D. M. Dwi Utami Putra, and P. W. Aditama, "Sales Forecasting Analysis Using Fuzzy Time Series and Simple Linear Regression Methods at Toko Ari," *Indones. J. Data Sci.*, vol. 6, no. 3, pp. 473–480, 2025, doi: <https://doi.org/10.56705/ijodas.v6i3.368> Research.
- [10] M. H. Widiyanto, R. Mayasari, F. I. Komputer, U. S. Karawang, and T. Timur, "IMPLEMENTASI TIME SERIES PADA DATA PENJUALAN DI GAIKINDO MENGGUNAKAN ALGORITMA SEASONAL ARIMA," *JATI (Jurnal Mhs. Tek. Inform.*, vol. 7, no. 3, pp. 1501–1506, 2023, doi: <https://doi.org/10.36040/jati.v7i3.6879>.
- [11] S. Ananth, K. Ghosh, P. . Sahal, and P. Jemima, "SALES PREDICTOR USING SIMPLE LINEAR REGRESSION AND SIMPLE MOVING AVERAGE MODEL," *Ijrasnet J. Res. Appl. Sci. Eng. Technol.*, pp. 1–6, 2023, doi: 10.2139/ssrn.4623389.
- [12] S. B. Fauzan, M. G. Efgivia, and A. Background, "Application of Business Intelligence to Prediction of Retail Product Demand in East Jakarta Using Linear Regression Algorithm," *Int. J. Sci. Eng. Sci.*, vol. 9, no. 5, pp. 69–72, 2025.
- [13] I. N. Rizki, M. L. Puspita, D. Prayoga, M. Q. Huda, and T. Selatan, "IMPLEMENTASI EXPLORATORY DATA ANALYSIS UNTUK ANALISIS DAN VISUALISASI DATA PENDERITA STROKE KALIMANTAN SELATAN MENGGUNAKAN PLATFORM TABLEAU," *JITET (Jurnal Inform. dan Tek. Elektro Ter.*, vol. 12, no. 1, pp. 560–567, 2024, doi: <http://dx.doi.org/10.23960/jitet.v12i1.3856> IMPLEMENTASI.
- [14] D. ES Barus, "Implementasi metode random forest untuk memprediksi penjualan produk," *J. TEKINKOM*, vol. 7, pp. 591–600, 2024, doi: 10.37600/tekinkom.v7i2.1510.
- [15] J. Nasional, S. Informasi, S. Hanifah, F. Akbar, and R. Pratama, "Implementasi Business Intelligence dan Prediksi Menggunakan Regresi Linear pada Data Penjualan dan Breakage di PT XYZ," *J. Nas. Teknol. dan Sist. Inf.*, vol. 08, no. 03, pp. 144–152, 2022, doi: <https://doi.org/10.25077/TEKNOSI.v8i3.2022.144-152>.