Journal of Information Systems and Informatics
Vol. 6, No. 3, September 2024 e-ISSN: 2656-4882 p-ISSN: 2656-5935
DOI: 10.51519/journalisi.v6i3.816 Published By DRPM-UBD

Enhancing Sales Performance through ARIMA-Based Predictive Modeling: Insights and Applications Model

Dwi Hartanti[1], Hanifah Permatasari[2]

[1,2]Information System Departement, Universitas Duta Bangsa Surakarta, Surakarta, Indonesia
Email: [1]dwihartanti@udb.ac.id, [2]hanifah_permatasari@udb.ac.id

Abstract

Gociko Snack, a Micro, Small, and Medium Enterprise (MSME), often faces significant challenges in managing its inventory due to the unpredictable nature of market demand. Accurate sales forecasting is crucial for Gociko Snack to optimize stock levels, reduce storage costs, and avoid out-of-stock or overstock situations. Traditional methods of sales prediction are often unable to cope with the dynamic and complex market environment in which Gociko Snack operates. in solving the case This research uses the ARIMA (AutoRegressive Integrated Moving Average) model for forecasting and application modeling using the CodeIgniter framework in a structured Waterfall system development methodology. Through rigorous testing and evaluation, the Mean Absolute Percentage Error (MAPE) was set at 9.18, which shows the effectiveness of the application in predicting sales trends with a high success rate. This research contributes valuable knowledge and practical solutions to empower businesses to navigate and utilize data-driven decision making for long-term success and resilience.

Keywords: Autoregressive Integrated Moving Average, ARIMA, Forecasting, Waterfall.

1. INTRODUCTION

In industries such as retail, food, railways, mining, tourism, energy, and cloud computing, accurate forecasting is essential for making informed decisions across short, medium, and long-term objectives. In these sectors, industrial application databases typically comprise related time series with shared key features, which support strategic planning and goal setting [1]. Analyzing time series data is crucial for extracting meaningful statistics and insights within a business context. Time series forecasting models, particularly valuable when time is a critical factor, significantly influence predicting future sales and managing business operations effectively [2, 3].

One of the most common models used for such forecasting is the Autoregressive Integrated Moving Average (ARIMA) model, which analyzes a time series by examining its past values, including lags and lagged prediction errors. This model is especially useful for forecasting future values of a non-stationary time series that

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

displays discernible patterns rather than irregularities [4]. Over the past decade, Artificial Intelligence (AI), particularly machine learning and deep learning, has made significant strides across various fields, including finance, healthcare, industry, retail, supply chain management, utilities, and networks [5]. Despite these advancements, traditional time series analysis and forecasting continue to predominantly rely on ARIMA models and their various adaptations [6].

However, traditional forecasting models like ARIMA often fail to adapt to the complexities and dynamic nature of certain market environments. For instance, Gociko Snack, a Micro, Small, and Medium Enterprise (MSME), sells dozens of kilos of snacks each month. The business faces significant challenges in managing inventory due to unpredictable market demand, which can fluctuate greatly. When Gociko Snack's inventory does not match actual market demand—either exceeding or falling short it results in financial losses due to unsold stock or missed sales opportunities [7]. These challenges highlight the need for more accurate sales forecasting to optimize stock levels, reduce storage costs, and avoid situations of either overstocking or running out of stock. Traditional sales prediction methods often fall short in addressing the dynamic and complex market environment in which Gociko Snack operates. Therefore, there is a pressing need for innovative approaches to improve the accuracy and reliability of sales forecasts [8].

This research aims to provide a comprehensive solution to Gociko Snack's sales forecasting challenges. By implementing the ARIMA model, the company is expected to enhance the precision of its sales predictions, positively impacting inventory management and daily operations. Additionally, the research seeks to develop an integrated information system to facilitate more effective data-driven decision-making. This system will help Gociko Snack monitor sales performance, manage stock levels optimally, and respond to market needs more quickly and accurately. With advanced prediction tools and an efficient management system, Gociko Snack will be better equipped to reduce operational risks and increase its competitiveness in the market. Ultimately, this study aims to contribute to the growth and sustainability of MSMEs by demonstrating that predictive technology and robust information management are key factors in achieving business success, especially amid dynamic and competitive market challenges.

Further studies have shown that financial markets, where stocks, bonds, securities, and currencies are traded daily, also generate time series data. The ARIMA model, along with other techniques like Exponential Smoothing and Neural Networks, is commonly used to analyze this data and predict stock prices by understanding past trends. For example, the research on daily NIFTY data implements three ARIMA variants—Basic, Trend-Based, and Wavelet-Based—to forecast future stock values [9]. The study's results have been integrated into an application system model developed using the CodeIgniter framework, chosen for its robustness and

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

rapid development capabilities while maintaining high performance [10]. The system's design ensures reliable data storage using the MariaDB Database Management System (DBMS), valued for its reliability, scalability, and open-source nature, making it suitable for an SME [11].

This application model will undergo further development to evolve into a comprehensive information system tailored to Gociko Snack's unique requirements. The information system aims to enhance various operational aspects, including inventory management, sales tracking, and customer relationship management. By integrating these functionalities, the system will provide a centralized platform for managing critical business operations, thereby improving efficiency and productivity. Furthermore, it will support data-driven decision-making by providing real-time insights and analytics based on historical and current data. This capability will enable Gociko Snack to make informed decisions regarding inventory replenishment, sales strategies, and market analysis, ultimately contributing to its overall growth and competitiveness in the market. The development of this information system underscores the importance of leveraging advanced technological solutions to meet the operational needs of SMEs, highlighting the potential for tailored information systems to drive business success and sustainability.

2. METHODS

2.1. Research Stages

The research flow designed to streamline the process, as illustrated in Figure 1.

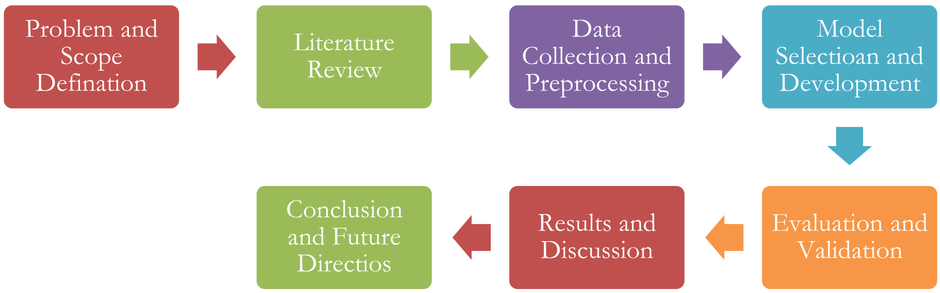


Figure 1. Research Flow

2.1.1 Problem Identification and Scope Definition

Define the need for a sales prediction information system at Gociko MSMEs. Identify specific challenges in sales forecasting, such as variability in demand and

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

inventory management inefficiencies. Clarify the objectives of developing the information system to improve forecasting accuracy and operational efficiency.

2.1.2 Literature Review

Conduct a comprehensive review of existing literature on sales prediction methods and information systems. Explore relevant studies on predictive modeling techniques like ARIMA, neural networks, and machine learning algorithms applied in similar contexts. Analyze case studies and best practices in implementing sales prediction systems in MSMEs to derive insights for the current study.

2.1.3 Data Collection and Preprocessing

Gather historical sales data from Gociko MSMEs over an extended period. Clean and preprocess the data to eliminate outliers, address missing values, and ensure consistency. Explore supplementary datasets, like economic indicators or seasonal factors, that might influence sales to improve prediction accuracy.

2.1.4 Model Selection and Development

Evaluate various predictive modeling techniques, focusing on suitability for time-series data and business needs. Select the ARIMA model as the primary method for its ability to capture temporal dependencies and forecast future sales trends. Develop the ARIMA model, including model specification, parameter estimation, and validation using historical data.

2.1.5 Implementation of the Information System

Design and develop the sales prediction information system based on the ARIMA model. Integrate the system with Gociko MSMEs' existing infrastructure and data management protocols. Ensure usability and accessibility of the system for stakeholders involved in sales forecasting and decision-making processes.

2.1.6 Evaluation and Validation

Evaluate the performance of the sales prediction information system against predefined metrics such as accuracy, precision, and computational efficiency. Validate the forecasts generated by comparing predicted sales with actual sales outcomes over a specified evaluation period. Conduct sensitivity analysis to assess the robustness of the ARIMA model under different scenarios and external influences.

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

2.1.7 Results and Discussion Interpretation

Discuss the findings from the evaluation and validation stages, highlighting the strengths and limitations of the developed information system. Interpret the implications of the results for Gociko MSMEs in terms of improving sales forecasting capabilities, optimizing inventory management, and enhancing business decision-making. Compare the performance of the ARIMA model with other predictive techniques considered during the literature review.

2.1.8 Conclusion and Future Directions

Summarize the key findings and contributions of the research in developing a sales prediction information system for Gociko MSMEs. Provide recommendations for further enhancements or refinements to the information system based on the study's insights and feedback. Outline potential future research directions, such as exploring advanced machine learning models or integrating real-time data for continuous improvement of sales forecasting accuracy.

2.2. System Development Model

In this research, the application development stage employs the Waterfall model, a structured approach widely adopted in software engineering for its sequential and systematic nature. This waterfall model was chosen because the stages are carried out sequentially and thoroughly[12], where each stage will be completed first, then can be continued to the next stage[13] which is carried out sequentially[14]. The Waterfall model advances through clearly defined stages, beginning with gathering and analyzing requirements, then moving to system design, implementation, testing, deployment, and finally, maintenance. Each phase is executed linearly, with progress contingent upon the completion of preceding stages, ensuring clarity and predictability in project timelines and deliverables. This structured approach not only enhances transparency and accountability throughout the development lifecycle but also aims to deliver a robust and reliable information system tailored to optimize sales forecasting and operational efficiencies within Gociko MSMEs.

The Waterfall model, a traditional software development methodology, follows a sequential and linear approach structured into distinct stages. It begins with requirements gathering and analysis which is critical in designing a system that meets user needs[15], where project requirements are identified, documented, and validated through consultation with stakeholders and end users. Once requirements are finalized, the system design phase follows, focusing on defining architecture, database structures, and overall system specifications based on gathered requirements. With design specifications in place, the implementation

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

phase commences, where the actual coding and development of the system occur according to the established design. Following implementation, the system undergoes rigorous testing in the validation phase, aiming to identify and rectify any defects or inconsistencies before deployment. Upon completing testing and validation, the deployment phase involves installing and launching the developed system in the operational environment. Finally, the maintenance phase ensures ongoing support, updates, and enhancements to the system post-deployment, addressing user feedback and evolving business needs over time. The Waterfall model's structured progression from requirements to maintenance offers clarity, predictability, and systematic control over each stage of the software development lifecycle, making it suitable for projects requiring thorough planning and sequential execution [16].

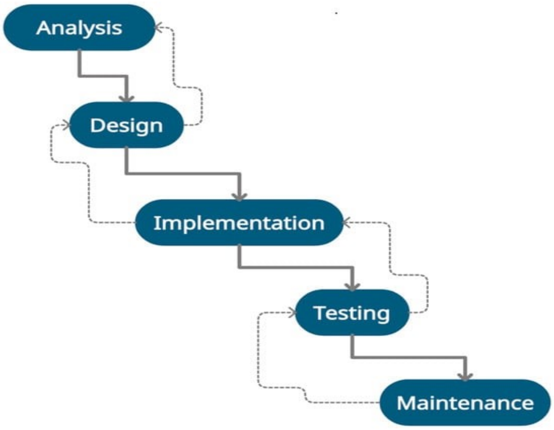


Figure 2. Waterfall Model

3. RESULTS AND DISCUSSION

3.1. ARIMA Model

The outline the stages of collecting sales data from Gociko MSMEs over two years, with data recorded monthly. This longitudinal data collection process is essential for capturing comprehensive sales trends and patterns, enabling a robust analysis of the company's performance over time. By systematically gathering and or two reorganizing this data, we aim to provide a solid foundation for subsequent predictive modeling and analysis, ultimately contributing to more informed decision-making and strategic planning for Gociko MSMEs. The consistency and regularity of monthly data intervals ensure that the dataset is both detailed and manageable, facilitating accurate and meaningful insights into the company's sales dynamics.

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

Table 1. Data Collection of Sales Results of Dried Chips Products

No	Period	Sales Yield (Kg)
1	Period 1	90,50
2	Period 2	105,00
3	Period 3	101,00
4	Period 4	120,00
5	Period 5	89,00
6	Period 6	115,50
7	Period 7	92,50
8	Period 8	80,50
9	Period 9	125,00
10	Period 10	95,50
11	Period 11	90,00
12	Period 12	103,5
13	Period 13	93,5
14	Period 14	98
15	Period 15	105
16	Period 16	107
17	Period 17	98,5
18	Period 18	110
19	Period 19	120
20	Period 20	105,5
21	Period 21	98,5
22	Period 22	115,5
23	Period 23	120,5
24	Period 24	110,5

The development of a sales result prediction table for Gociko MSMEs. This predictive tool is designed to provide accurate forecasts of future sales based on historical data, enabling Gociko to make informed decisions about inventory management, production planning, and market strategies. The prediction table is constructed using advanced statistical models and data analysis techniques to ensure reliability and precision. By integrating this predictive capability into their operations, Gociko MSMEs can anticipate market demands more effectively, reduce the risks associated with overstocking or understocking, and optimize overall business performance. This approach underscores the critical role of data-driven decision-making in enhancing the competitiveness and sustainability of MSMEs in a dynamic market environment.

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

The next stage is the calculation to determine the value of the regression coefficient. In this study, to make it easier to understand, the researcher attached a table of the results of the calculation of the forecasting value by determining the values of X and Y where the determination of the value of X times Y and X to the power of 2 is carried out.

Table 2. Calculation of Forecasting Values

Period	Yt	Xt	XY	X^2
1	90,50		0	0
2	105,00	90,50	9502,5	8190,25
3	101,00	105,00	10605	11025
4	120,00	101,00	12120	10201
5	89,00	120,00	10680	14400
6	115,50	89,00	10279,5	7921
7	92,50	115,50	10683,75	13340,25
8	80,50	92,50	7446,25	8556,25
9	125,00	80,50	10062,5	6480,25
10	95,50	125,00	11937,5	15625
11	90,00	95,50	8595	9120,25
12	103,50	90,00	9315	8100
13	93,50	103,50	9677,25	10712,25
14	98,00	93,50	9163	8742,25
15	105,00	98,00	10290	9604
16	107,00	105,00	11235	11025
17	98,50	107,00	10539,5	11449
18	110,00	98,50	10835	9702,25
19	120,00	110,00	13200	12100
20	105,50	120,00	12660	14400
21	98,50	105,50	10391,75	11130,25
22	115,50	98,50	11376,75	9702,25
23	120,50	115,50	13917,75	13340,25
24	110,50	120,50	13315,25	14520,25
Total	2490,5	2380	247828,3	249387

The next step involves the calculation process to determine the value of Regression Coefficient 1 in ARIMA Model [17]. This coefficient is a crucial parameter in the regression analysis, representing the relationship between the independent variable and the dependent variable. The formula for determining

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

Regression Coefficient 1 This calculation is essential for constructing an accurate regression model, which in turn facilitates reliable predictions and insights based on the analyzed data. By determining Regression Coefficient 1, we can better understand the degree of impact that changes in the independent variable have on the dependent variable, thereby enhancing the precision of our predictive models for Gociko MSMEs.

$$\varnothing_1 = \frac{n\sum_{i=1}^{n} X_i\ Y_i - \sum_{i=1}^{n} X_i\ \sum_{i=1}^{n} Y_i}{\sum_{i=1}^{n} X_i^2 - \left(\sum_{i=1}^{n} X_i\right)^2} \quad (1)$$

Based on Table 2 calculation of forecasting values use Equation 1, the steps to determine the value of regression coefficient 1 are as follows.

$$\varnothing_1 = \frac{(24 \times 247828)-(2380 \times 2490,5)}{(24 \times 249387)-(2380^2)}$$

$$\varnothing_1 = 0,06385$$

The calculation process is conducted to determine the value of Regression Coefficient 0. This coefficient represents the intercept in regression analysis, indicating the value of the dependent variable when the independent variable is zero, as shown in Equation 2. This computation is essential for constructing an accurate regression model, facilitating predictions and interpreting the relationship between these variables within the analytical framework applied to Gociko MSMEs.

$$\varnothing_0 = \frac{1}{n}\left(\sum Y_i - \varnothing_1 \sum X_i\right) \quad (2)$$

$$\varnothing_0 = \frac{2490,5-(0,06385 \times 2380)}{24}$$

$$= 97,43$$

Determining the Autoregressive Value of the number of sales at Gociko. The next step is to determine the forecasting value for the next period. The formulas and calculations are as shown in Equation 3.

$$Y_t = \varnothing_1 + \varnothing_1\ Y_{t-1} + \varnothing_2\ Y_{t-2} + \ldots + \varnothing_p\ Y_{t-p} + e_t \quad (3)$$

By using simplification in determining the regression coefficient value, the following calculation results are obtained

$$Y_t = \left(97,43 + (0,06383 \times 110,50)\right) + 0,9827 = 105,47$$

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

Next step Determine the Forecasting Value with Autoregressive Integration with Moving Average (ARIMA) use Equation 4.

$$ARIMA = \left(\left(\frac{1}{n}\right).Yt + Y_{t-1} + Y_{t-n}\right) \quad (4)$$

$$= \left(\left(\frac{1}{n}\right).120{,}5 + 110{,}5 + 105{,}47\right)$$
$$= 112{,}16$$

Based on the prediction results obtained using the ARIMA method, it is evident that the sales forecast for the January 2024 period amounts to 112.16 kilograms. This outcome underscores the effectiveness of the ARIMA model in forecasting sales trends for Gociko MSMEs, providing valuable insights into future demand patterns. Such predictive capabilities enable businesses to proactively adjust inventory levels, optimize resource allocation, and enhance operational efficiency. These findings highlight the importance of utilizing advanced statistical techniques to support informed decision-making processes and ensure sustained growth and competitiveness in dynamic market environments.

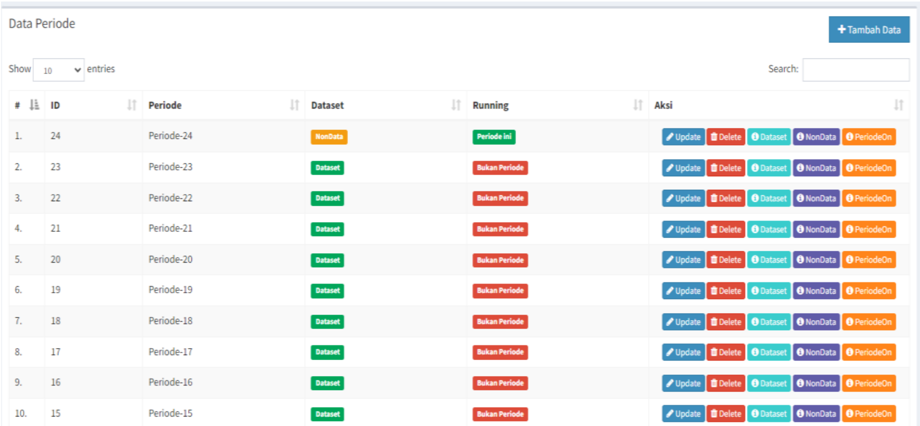
3.2. Application Development Model

The outcomes of developing applications focused on the prediction period data management feature are significant, as shown in Figure 3. These findings underscore the effectiveness of enhancing data handling capabilities for predictive analytics. The application's implementation of advanced data management features facilitates systematic storage, retrieval, and analysis of both historical and real-time data, which is crucial for accurate forecasting and decision-making processes. By integrating predictive models into the application framework, stakeholders at Gociko MSMEs benefit from improved insights into future trends and demand patterns. This approach not only enhances operational efficiencies but also supports proactive strategies in inventory management and resource allocation. The results emphasize the pivotal role of robust data management systems in empowering businesses to adapt swiftly to market dynamics and optimize performance metrics, contributing to sustained competitiveness and operational excellence.

In examining the outcomes of integrating the ARIMA (AutoRegressive Integrated Moving Average) model into predictive analysis applications, as depicted in Figure 4, notable insights emerge regarding its efficacy in forecasting sales trends. The application of ARIMA has demonstrated significant capabilities in capturing and analyzing time-series data, thereby enabling accurate predictions of future sales for Gociko MSMEs. By leveraging ARIMA's ability to account for temporal dependencies and seasonality in sales data, the application enhances decision-

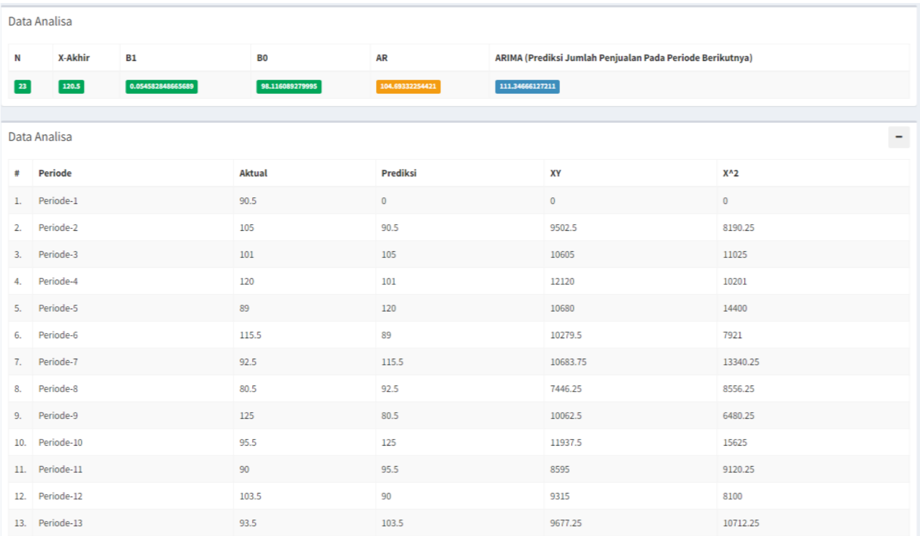
p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

making processes related to inventory management, production planning, and strategic resource allocation. These results underscore the importance of utilizing advanced statistical techniques to enhance predictive accuracy and operational efficiency within MSME contexts. The integration of ARIMA within predictive analysis applications not only facilitates proactive business strategies but also fosters a data-driven approach to optimizing performance and maintaining competitiveness in dynamic market environments.


Data Periode
+ Tambah Data
Show 10 entries Search:

#	ID	Periode	Dataset	Running	Aksi
1.	24	Periode-24	NonData	Periode ini	Update Delete Dataset NonData PeriodeOn
2.	23	Periode-23	Dataset	Bukan Periode	Update Delete Dataset NonData PeriodeOn
3.	22	Periode-22	Dataset	Bukan Periode	Update Delete Dataset NonData PeriodeOn
4.	21	Periode-21	Dataset	Bukan Periode	Update Delete Dataset NonData PeriodeOn
5.	20	Periode-20	Dataset	Bukan Periode	Update Delete Dataset NonData PeriodeOn
6.	19	Periode-19	Dataset	Bukan Periode	Update Delete Dataset NonData PeriodeOn
7.	18	Periode-18	Dataset	Bukan Periode	Update Delete Dataset NonData PeriodeOn
8.	17	Periode-17	Dataset	Bukan Periode	Update Delete Dataset NonData PeriodeOn
9.	16	Periode-16	Dataset	Bukan Periode	Update Delete Dataset NonData PeriodeOn
10.	15	Periode-15	Dataset	Bukan Periode	Update Delete Dataset NonData PeriodeOn

Figure 3. Period Feature


Data Analisa

N	X-Akhir	B1	B0	AR	ARIMA (Prediksi Jumlah Penjualan Pada Periode Berikutnya)
23	120.5	0.054582848665689	98.116089279995	104.69332254421	111.34666127211

Data Analisa

#	Periode	Aktual	Prediksi	XY	X^2
1.	Periode-1	90.5	0	0	0
2.	Periode-2	105	90.5	9502.5	8190.25
3.	Periode-3	101	105	10605	11025
4.	Periode-4	120	101	12120	10201
5.	Periode-5	89	120	10680	14400
6.	Periode-6	115.5	89	10279.5	7921
7.	Periode-7	92.5	115.5	10683.75	13340.25
8.	Periode-8	80.5	92.5	7446.25	8556.25
9.	Periode-9	125	80.5	10062.5	6480.25
10.	Periode-10	95.5	125	11937.5	15625
11.	Periode-11	90	95.5	8595	9120.25
12.	Periode-12	103.5	90	9315	8100
13.	Periode-13	93.5	103.5	9677.25	10712.25

Figure 4. Pediction Result

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

3.3. Testing with MAPE

The accuracy of the forecasts was assessed using the mean absolute percentage error (MAPE) [18]. This metric, expressed as a percentage, quantifies the absolute difference between predicted and actual values relative to the actual value itself. Unlike the mean percentage error (MPE), which considers both positive and negative deviations from actual values, MAPE focuses solely on the magnitude of the error, ensuring a straightforward assessment of prediction accuracy. MAPE provides a direction-agnostic measure, emphasizing the scale of forecasting errors irrespective of their positive or negative nature. A higher MAPE indicates less accurate forecasts, while a lower MAPE signifies higher prediction accuracy. The calculation formula for MAPE is represented as shown in Equation 5.

$$MAPE = \frac{100}{n} \sum \left| \frac{A_t - F_t}{A_t} \right| \quad (5)$$

Based on the MAPE formula, we evaluated the forecasting accuracy using sales data from six months in 2024. The MAPE results are summarized in the following table, illustrating the percentage difference between predicted and actual sales values for each month. MAPE serves as a reliable metric to assess the precision of our predictive models, offering insights into the effectiveness of forecasting methods utilized in this study. A lower MAPE value indicates closer alignment between predicted and actual sales figures, signifying higher accuracy in our forecasts. This analysis highlights the application of MAPE as a pivotal tool in evaluating and refining predictive models, essential for enhancing decision-making processes and operational strategies within Gociko MSMEs.

Table 3 MAPE Testing Results.

No	Period	Actual	ARIMA	Error	Absolut Error Value	Absolute Error value divided by Actual value
		y	y'	y-y'	|y-y'|	| (y-y')/y|
1	25	115,00	112,61	2,390	2,390	0,0207826
2	26	90,00	110,00	-20,000	20,000	0,2222222
3	27	105,50	116,50	-11,000	11,000	0,1042654
4	28	130,00	114,76	15,240	15,240	0,1172308
5	29	112,00	118,60	-6,600	6,600	0,0589286
6	30	120,00	116,71	3,290	3,290	0,0274167
			Total			**0,5508**
			MAPE (N=6)			**9,18**

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

3.4. Discussion

Recent research on sales prediction using the ARIMA model has demonstrated an error rate of 0.05363, showcasing its effectiveness for certain types of data [19]. Another study confirms that ARIMA is particularly suitable for linear data patterns [20]. However, traditional ARIMA models often assume that residual sequences are white noise, which is not always accurate and can lead to forecasting errors. To address this limitation, an optimized sales forecasting model was developed by combining the ARIMA model with an adaptive resonance neural network (ART2). This approach improves prediction accuracy by using ART2 to process, categorize, and adjust residual sequences, effectively managing autocorrelation and volatility in the residuals to provide a more accurate representation of sales patterns. The enhanced BEST-ARIMA model, incorporating these techniques, outperforms the standard ARIMA model, as indicated by lower error rates in experimental results [21].

The research conducted for Gociko MSMEs supports these findings by demonstrating that ARIMA can be effectively applied to forecast sales trends using historical data collected over two years. This longitudinal data, recorded monthly, captures comprehensive sales trends and patterns, providing a robust foundation for predictive modeling. For example, the sales data of dried chip products from Gociko MSMEs, shown in Table 1, enabled the development of a prediction model that forecasted future sales with high accuracy, allowing Gociko to make informed decisions about inventory management, production planning, and market strategies. By systematically gathering and reorganizing this data, Gociko achieved a lower mean absolute percentage error (MAPE) of 9.18%, illustrating the model's precision and reliability in predicting future sales [18].

Further studies highlight that accurate sales forecasting is vital for modern business intelligence, particularly in inventory management and staff scheduling, which directly impacts sales performance and customer satisfaction. For instance, a comparison of the ARIMA model, Facebook's Prophet Model, and the XGBoost Model found that ARIMA achieved the lowest Root Mean Square Error (RMSE) value of 739.06, proving it to be the most accurate model for that context [22]. Additionally, an enhanced ARIMA model applied to monthly chemical sales data in the United States showed its flexibility in capturing different forms of autocorrelation, although it requires a stationary time series with no trend or seasonality [23].

There is no universally optimal method for solving time-series forecasting challenges, as each situation may require a different approach [24]. Basic techniques like the Moving Average (MA) method are useful for time-series data without significant seasonal patterns [25]. More advanced methods, like ARIMA, have been successfully used to forecast various scenarios, including retail sales of

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

women's footwear with seasonal demand fluctuations (e.g., increased boot purchases during winter) [26, 27]. Other studies have applied multivariate ARIMA models to forecast the demand for perishable goods [28] and combined ARIMA with neural networks to predict network traffic and cryptocurrency prices, taking into account external factors such as social media influence [29].

The results from the Gociko MSMEs study align with this broader research, demonstrating that integrating advanced predictive models like ARIMA into a robust data management framework can significantly enhance forecasting accuracy and operational decision-making. The study emphasizes the importance of consistent data collection and analysis to optimize inventory levels, resource allocation, and overall business performance, reinforcing the critical role of data-driven strategies in sustaining competitiveness and growth in dynamic market environments.

4. CONCLUSION

This study successfully demonstrates the effectiveness of integrating advanced predictive tools to enhance operational efficiency, optimize resource allocation, and promote sustainable growth in a competitive market. The developed application, built using the CodeIgniter framework, accurately forecasted the upcoming period's sales at 112.61 units, highlighting its capability to address Gociko's specific forecasting needs. The model's robustness is further evidenced by a Mean Absolute Percentage Error (MAPE) of 9.18, indicating a high degree of precision in predicting sales trends. These results emphasize the critical role of advanced technological frameworks and rigorous testing protocols in supporting decision-making processes, improving inventory management, and enabling proactive responses to market dynamics for small and medium-sized enterprises. Future research could focus on refining the model by incorporating additional data sources and advanced analytical techniques to further enhance forecasting accuracy and operational effectiveness in ever-changing business environments.

ACKNOWLEDGEMENT

The author would like to thank the Directorate of Research, Technology, and Community Service and the Ministry of Education, Culture, Research, and Technology for funding the PDP scheme research in the implementation year 2024 and not forgetting Duta Bangsa University Surakarta.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

REFERENCES

[1] K. Bandara, H. Hewamalage, Y. H. Liu, Y. Kang, and C. Bergmeir, "Improving the accuracy of global forecasting models using time series data augmentation," *Pattern Recognit.*, vol. 120, p. 108148, 2021.
[2] J. F. Torres, D. Hadjout, A. Sebaa, F. Martínez-Álvarez, and A. Troncoso, "Deep learning for time series forecasting: a survey," *Big Data*, vol. 9, no. 1, pp. 3–21, 2021.
[3] B. K. Jha and S. Pande, "Time series forecasting model for supermarket sales using FB-Prophet," in *2021 5th International Conference on Computing Methodologies and Communication (ICCMC)*, IEEE, 2021, pp. 547–554.
[4] U. M. Sirisha, M. C. Belavagi, and G. Attigeri, "Profit prediction using ARIMA, SARIMA, and LSTM models in time series forecasting: A comparison," *IEEE Access*, vol. 10, pp. 124715–124727, 2022.
[5] I. M. Enholm, E. Papagiannidis, P. Mikalef, and J. Krogstie, "Artificial intelligence and business value: A literature review," *Inf. Syst. Front.*, vol. 24, no. 5, pp. 1709–1734, 2022.
[6] V. I. Kontopoulou, A. D. Panagopoulos, I. Kakkos, and G. K. Matsopoulos, "A review of ARIMA vs. machine learning approaches for time series forecasting in data-driven networks," *Future Internet*, vol. 15, no. 8, p. 255, 2023.
[7] B. Wiryawan Yudanto, B. Hartanto, and S. Nusantara, "Implementasi Metode Single Exponential Smoothing Dalam Melakukan Perkiraan Stok Barang Di Toko Makanan Ringan Berbasis Sistem Informasi," *Manag. Account. Technol. (Jematech)*, vol. 5, no. 2, 2022.
[8] B. Hartanto and S. Tomo, "Sistem Pengelompokan Siswa Berdasarkan Tingkat Kedisiplinan Menggunakan Metode Naïve Bayes Classifier," *J. Teknol. Inform. Komun. (TIKomSiN)*, vol. 9, no. 2, pp. 50–55, 2021.
[9] B. Dhyani, M. Kumar, P. Verma, and A. Jain, "Stock market forecasting technique using ARIMA model," *Int. J. Recent Technol. Eng. (IJRTE)*, vol. 8, no. 6, pp. 2694–2697, 2020.
[10] A. F. Sallaby and I. Kanedi, "Perancangan Sistem Informasi Jadwal Dokter Menggunakan Framework Codeigniter," *J. Media Infotama*, vol. 16, no. 1, 2020.
[11] O. Izquierdo-Monge, G. Martin-Jimenez, and P. Peña-Carro, "Development and improvement of a data storage system in a microgrid environment with HomeAssistant and MariaDB," in *Ibero-American Congress of Smart Cities*, Springer, 2021, pp. 273–284.
[12] D. H. Jayadinata, A. T. Pratama, and T. D. Sofianti, "Development of performance monitoring dashboard for product packaging manufacturer by using Waterfall methodology," 2014, p. 6869.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

[13] N. Hidayati, "Development of goods purchase information system using the Waterfall model," *Int. J. Inf. Syst. Technol. Akreditasi*, vol. 6, no. 158, pp. 548–560, 2022.
[14] A. Saravanos and M. X. Curinga, "Simulating the software development lifecycle: The Waterfall model," *Appl. Syst. Innov.*, vol. 6, no. 6, 2023.
[15] H. J. Christanto and Y. A. Singgalen, "Analysis and design of student guidance information system through software development life cycle (SDLC) and Waterfall model," *J. Inf. Syst. Inform.*, vol. 5, no. 1, pp. 259–270, 2023.
[16] A. Saravanos and M. X. Curinga, "Simulating the software development lifecycle: The Waterfall model," *Appl. Syst. Innov.*, vol. 6, no. 6, p. 108, 2023.
[17] J. Contreras, R. Espinola, F. J. Nogales, and A. J. Conejo, "ARIMA models to predict next-day electricity prices," *IEEE Trans. Power Syst.*, vol. 18, no. 3, pp. 1014–1020, 2003.
[18] S. Jeong, "Forecast accuracy of demand for registered nurses and its determinants in South Korea," *Hum. Resour. Health*, vol. 22, no. 1, p. 44, 2024.
[19] T. Bowen, Z. Zhe, and Y. Zulin, "Forecasting method of e-commerce cargo sales based on ARIMA-BP model," in *2020 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA)*, IEEE, 2020, pp. 133–136.
[20] Z. Huo, "Sales prediction based on machine learning," in *2021 2nd International Conference on E-Commerce and Internet Technology (ECIT)*, IEEE, 2021, pp. 410–415.
[21] W. Hu and X. Zhang, "Commodity sales forecast based on ARIMA model residual optimization," in *2020 5th International Conference on Communication, Image and Signal Processing (CCISP)*, IEEE, 2020, pp. 229–233.
[22] S. Ratre and J. Jayaraj, "Sales prediction using ARIMA, Facebook's Prophet and XGBoost model of machine learning," in *Machine Learning, Image Processing, Network Security and Data Sciences: Select Proceedings of 3rd International Conference on MIND 2021*, Springer, 2023, pp. 101–111.
[23] O. M. Salah, G. J. M. Mahdi, and I. A. A. Al-Latif, "A modified ARIMA model for forecasting chemical sales in the USA," in *J. Phys.: Conf. Ser.*, IOP Publishing, 2021, p. 032008.
[24] G. P. Zhang and D. M. Kline, "Quarterly time-series forecasting with neural networks," *IEEE Trans. Neural Netw.*, vol. 18, no. 6, pp. 1800–1814, 2007.
[25] S. Chopra and P. Meindl, *Supply Chain Management: Strategy, Planning & Operation*. Springer, 2007.
[26] P. Ramos, N. Santos, and R. Rebelo, "Performance of state space and ARIMA models for consumer retail sales forecasting," *Robot. Comput. Integr. Manuf.*, vol. 34, pp. 151–163, 2015.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

[27] J. Huber, A. Gossmann, and H. Stuckenschmidt, "Cluster-based hierarchical demand forecasting for perishable goods," *Expert Syst. Appl.*, vol. 76, pp. 140–151, 2017.
[28] H. Yang, X. Li, W. Qiang, Y. Zhao, W. Zhang, and C. Tang, "A network traffic forecasting method based on SA optimized ARIMA–BP neural network," *Comput. Netw.*, vol. 193, p. 108102, 2021.
[29] C. Tandon, S. Revankar, and S. S. Parihar, "How can we predict the impact of social media messages on the value of cryptocurrency? Insights from big data analytics," *Int. J. Inf. Manag. Data Insights*, vol. 1, no. 2, p. 100035, 2021.