Demand Forecasting on Sales at Grocery Stores using a Data Science Approach

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Abstract
This study tries to present the application of predictive analysis to forecast sales transaction data for the next month. The analysis results are presented in the form of graphs and tables to provide a more comprehensive picture of each product's sales patterns and trends. Based on the graph presented, it can be seen that some types of merchandise do not experience sales activity in certain months. This can affect forecasting results, as analytical models cannot capture unstable or consistent sales patterns for those products. Fluctuations and instability in sales data can cause difficulties for predictive models in producing accurate forecasts. From the observation results, the ARIMA and Exponential Smoothing models have shown relatively good accuracy with a MAPE value of 23.646% in rice merchandise. All merchandise shows quite good results, but the accuracy value reaches 58.509% in sugar merchandise. This is because sugar sales data shows higher fluctuations and is unstable, making it more difficult for predictive models to produce accurate forecasts. Economic conditions, consumer trends, and market competition can affect sugar sales patterns and cause difficulties in modelling.

Keywords:
ARIMA;
Data Science;
Demand Forecasting;
Exponential Smoothing;
VUCA

1. Introduction

The research focuses on demand forecasting in the trading business sector, which is an essential topic in business today. Accurate demand forecasting can help trading companies optimize production processes and inventory management and develop new products based on market needs. In an increasingly complex and uncertain business environment, the ability to forecast future demand is crucial for company leaders to make strategic decisions. This study will explore using data science approaches, such as the ARIMA (Autoregressive Integrated Moving Average) and Exponential Smoothing methods, to produce more accurate demand forecasting. Using good data quality, this research will provide valuable insights for business leaders facing VUCA (Volatility, Uncertainty, Complexity, Ambiguity) challenges.

Development challenges in the business world, regional, national, and international, continue to be endless. Business today is in an era called VUCA, which requires business people to make the right decisions when facing the challenges that arise. The current business situation is difficult to predict due to rapid development, which creates uncertainty about the truth and reality. In today's VUCA era, changes occur very quickly and unexpectedly and are influenced by many complicated factors. Truth and reality become very subjective. The development of technology and information is one of the biggest influences of this change, creating uncertainty and volatility for business leaders (Rofiqi & Mukhlis, 2023).

The difficulty of predicting the future and the complexity of the challenges faced by business people are the main characteristics of today's VUCA era. In this context, business leaders must make quick and appropriate decisions, although they often have to be made with limited information. In the VUCA era, which is full of fast, unpredictable changes and influenced by many complicated factors, the maximum use of advanced technology is essential to control and master the situation well.

Technological advances that continue to evolve have led to significant changes around the world today, affecting various aspects of life and Business (Rani Afkarina et al., 2023).

The decisions taken by business leaders have a significant impact on the sustainability and growth of the company. In today's uncertain environment, the quality of decisions is becoming increasingly crucial. One of the critical factors that can help business leaders make better decisions is data. Data quality has a strong and positive correlation with the quality of strategic decision-making at the top management level. Conversely, poor data quality negatively impacts the quality of decisions, hindering effective strategies and efficient management. Good data quality has a strong and positive correlation with the quality of strategic decision-making at the top management level, one of which is Business Leaders (Abu-AlSondos, 2023). Quality data can provide accurate information and insights, thus supporting better and more effective decision-making.

Conversely, poor data quality can negatively impact the quality of decisions, hinder effective strategies, and make it difficult to manage efficiently (Trinh & Tran, 2023). Therefore, ensuring data quality is critical for business leaders in today's uncertain environment. *Demand* forecasting can be a solution to overcome uncertainty in business because by utilizing good data quality, companies can make more effective strategic decisions in planning production, managing inventory, and developing new products according to market needs.

Accurate demand forecasting is essential for businesses to plan production efficiently and profitably. By accurately predicting future customer needs, companies can optimize production processes, manage inventory, and develop new products that meet market demand (Keiser & Tortora, 2022). This aligns with the importance of data quality in strategic decision-making for business leaders. Demand forecasting is a predictive analysis that estimates how many products or services customers will need in the future so that this information can be used to support better and more effective business decisions (M K et al., 2023). By utilizing technology in Data Science companies can analyze historical and real-time data to produce more accurate forecasting. This information can be used in strategic decision-making, such as production planning, inventory management, and new product development.

Data Science can lead to critical decision-making using a data-driven approach, identifying related concepts, principles, and capabilities for different Business use cases (Singh Yadav et al., 2022). This aligns with the importance of data quality in strategic decision-making for business leaders. By utilizing technology in *Data Science*, companies can analyze historical and real-time data to produce more accurate forecasts. Data science can help by analyzing stored data and revealing meaningful trends, making it a helpful technology for decision-making (Bhatnagar et al., 2022). Data Time Series can provide insight into historical patterns and help develop more accurate projections. This information can be used in strategic decision-making, such as production planning, inventory management, and new product development.

Data *Time Series* can provide insights into developing more accurate projections (Hou et al., 2024), which aligns with the importance of data quality in strategic decision-making for business leaders. By identifying and modelling the intrinsic factors underlying sparse relationship patterns and accurate predictions, time series forecasting can provide deeper insights and better insights into future operations and strategic planning. It transforms data into actionable insights for predictive maintenance, production optimization, sales forecasting, and anomaly detection (Kashpruk et al., 2023).

Research on demand forecasting is an important topic because it directly impacts business success for large companies and trading business units. In an environment full of uncertainty, the ability to forecast future customer needs can provide a competitive advantage. Accurate demand forecasting allows companies to optimize production, merchandise inventory management, and product development, which aligns with the importance of data quality in strategic decision-making for business leaders. Real-time and historical data analysis using data science technology can produce more accurate forecasting, which can be used for important planning, operations, and innovation decisions. Thus, demand forecasting research is precious for organizations that want to survive and thrive. Some research related to forecasting demand or sales using various data analysis methods will be explained further in the next paragraph.

In every business activity, demand forecasting is needed to determine product demand and plan and control a product. Demand forecasting should not only be used by very well-known companies (Rau et al., 2018). Companies still in the form of trading units must also make forecasts so that the number of products produced can meet consumer demand. Another reason a trading business must do forecasting is that operations can run smoothly and the company can compete with other companies. According to Van Donselaar et al. (Dalimunthe et al., 2023), demand forecasting is a challenge for producers because it affects the decision-making of an operational system. In addition, Yue et al., Bertaglia, Martinez et al., and Arvan et al. also said that demand forecasting is essential in supply chain management because it affects competitiveness and profitability and provides important information for purchasing decisions, production, inventory levels, logistics, finance, and marketing. If the forecasting error is relatively small, the results are considered efficient. However, if the forecast error is too low, the product inventory stock will be limited, causing customer demand to be unmet. Therefore, it is crucial to be careful when choosing the most efficient calculation method when conducting forecasting.

In forecasting, several methods can be used, including ARIMA (Autoregressive Integrated Moving Average). Wei WWS said that the ARIMA Method consists of the Autoregressive (AR) and Moving Average (MA) methods combined with the differentiation process (Vista Magdalena Sihombing et al., 2022). However, the ARIMA method has weaknesses, including decreased accuracy in predicting time series data with nonlinear components. In general, ARIMA is symbolized by ARIMA (p,d,q), where p indicates the order of autoregressive (AR), d is the degree of difference of the process, and q denotes the order/degree of moving average (MA). Also, research conducted by (Fadhillah et al., 2024), showed that ARIMA plays an essential role in this study because of its ability to capture linear patterns in Bank Mandiri stock data, which is the primary basis for accurate forecasting. As part of the ARIMA-ANN hybrid method, ARIMA helps identify linear trends and patterns in stock price data while ANN processes its nonlinear components. By forming an ARIMA (0,1,1) model, this study successfully separates the linear part of the data so that ANN can handle the residual or remainder of the ARIMA model more effectively. In this approach, ARIMA is essential because it ensures that the linear component is dealt with well before the ANN model is applied to the nonlinear part. This results in perfect forecasting accuracy, as evidenced by the MAPE value below 10%.

In addition, the exponential smoothing method can be used in forecasting. This method is fairly good for short-, medium-, or long-term forecasting(Sarungu & Iskandar, 2024). In this study, Exponential Smoothing is considered a better method than Moving Average in forecasting because it has a lower error rate, which means the prediction results are more accurate. Based on the comparison table, Exponential Smoothing with $\alpha = 0.04$ produces the most minor error value, namely MAD of 82.88061, MSE of 19,786.65, and MAPE of 62%. This shows that the Exponential Smoothing method is more appropriate for this study because it produces more accurate estimates with minimal error rates.

This study aims to develop a demand forecasting model using ARIMA and Exponential Smoothing methods. This study will use data on basic sales transactions to produce short-term forecasting using ARIMA. Furthermore, the results of the ARIMA forecast will be further processed by the Exponential Smoothing method to produce a relatively more stable prediction. This aligns with the importance of data quality in strategic decision-making for business leaders, where accurate demand forecasting can help companies plan production, manage inventory, and develop new products that suit market needs, especially in today's uncertain business environment.

2. Method

This research will conduct predictive analysis in business decision-making using demand forecasting methods and scientific data analysis. A store sales dataset from the Kaggle data science competition will be used for the analysis, covering a time series of daily transactions from January 2020 to April 2021, consisting of 1289 rows of data. This can help trading business owners plan, manage inventory, and provide merchandise according to market needs. The methodology in this study will use RapidMiner, a tool for data scientists that provides more than 1500 native algorithms, data preparation functions, and data science functions, as well as supporting machine learning libraries and integrating Python and R code (Bjaoui et al., 2020). RapidMiner was chosen for its ability to import, process, and analyze data quickly and efficiently. It allows users to perform various data analysis steps in one integrated environment, such as data cleaning, transformation, modelling, and evaluation (Kotu & Deshpande, 2015). This tool will be used in the data preparation and sales forecasting stages to optimise the analysis process and generate actionable insights to improve business decision-making. The stages in this Research are shown in Figure 1.

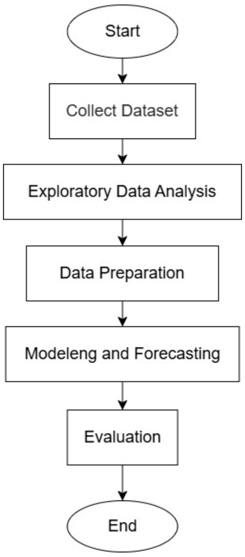

Figure 1. Research Stages

1. Data Sets

The dataset used was obtained from Kaggle and uploaded by a user named Bejo Pamungkas. The dataset is titled "Grocery store purchase and sales data" and consists of daily transaction time series data from January 2020 to April 2021, totalling 1289 rows of data.

2. EDA

Exploratory Data Analysis (EDA) is the initial stage in building a model, which is an integral part of the data science process and represents how to conduct statistical analysis carried out in analyzing confirmatory data related to modelling and hypotheses. In conducting EDA, the activities include data visualization, descriptive statistical analysis, and understanding the nature of time-sequence data. A good understanding of the data will help choose the suitable forecasting model (Tanuwidjaja & Widjaja, 2020)

3. Data Preparation

Data preparation: At this stage, the sales data will be cleaned, changed, and prepared for further analysis. This process includes handling missing values, handling outliers, and ensuring the appropriate data format. In this case, the tool used is RapidMiner, which adjusts the existing importer features according to the needs of the analysis process.

4. Sales Forecasting

This stage uses ARIMA and Exponential Smoothing. Two algorithmic models are used at this stage. ARIMA predicts short-term sales, while Exponential Smoothing stabilizes ARIMA's forecasting results to obtain a relatively more stable forecast value.

In this study, the ARIMA model was used where:

p = 1, indicating the order of autoregressive components is 1

d = 0, indicating no differentiation process

q = 0, indicating the order of the moving average element is 0

This ARIMA model was chosen because residuals were analyzed to determine how much error was contained in the model. By examining the residuals, we can evaluate how well the ARIMA model can capture patterns and variations in the data. Residuals with values close to zero indicate that the model is good enough at capturing data patterns to produce accurate forecasting. Therefore, residual analysis is important in choosing the most appropriate ARIMA model. A good residual is characterized by a large number of values close to 0, which indicates that the model is good enough to capture patterns in the data (Ningrum et al., 2022). Therefore, higher AR(p) and MA(q) must be applied cautiously, as they can increase the risk of including irrelevant variability in the model. However, a simple model with only an AR component is often sufficient to capture the archetype in the time series data, especially if the residuals are low (Hyndman & Athanasopoulos, 2021). Exponential Smoothing is used in forecasting methods that are pretty good in short, medium, or long-term forecasting.

$$F_t = F_{t-1} + \alpha(A_{t-1}F_{t-1}) \quad (1)$$

with the caption:
F_t: Forecast value of the time period t-1
F_{t-1} : the value of the forecast of the time period t
A_{t-1} : the actual value for the time period t
A : smoothing constant

Evaluation of forecasting results will be carried out using MAPE (Mean Absolute Percentage Error) to assess the model's performance and select the best forecasting results. The formula for MAPE is as follows:

$$M = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \quad (2)$$

Where:
M = average percentage of absolute errors
n = the frequency at which the summation iteration occurs
A_t = Actual value
F_t = Estimated value

3. Results and Discussion

3.1 Results

A. Collect Dataset

The data obtained for this analysis is a store sales dataset derived from the Kaggle data science competition. This dataset consists of a time series of data on daily store transactions from January 2020 to April 2021, totalling 1289 rows of data. Datasets contain columns; date (tanggal), buyer's name (nama.pembeli), item's name (nama.barang), quantum (kuantum), and nominal. This data will be used to conduct predictive analysis and assist store owners in planning in Rapidminer.

B. EDA

Three things were selected for further analysis from the existing data set: date, item name, and quantity. Graphs present information about the frequency distribution of an event or data over a given time, which can provide valuable insights into patterns and trends in this data set. Based on the histogram in Figure 2, the dataset covers the period from January 2020 to April 2021, with a total of 1289 rows of daily transaction data.

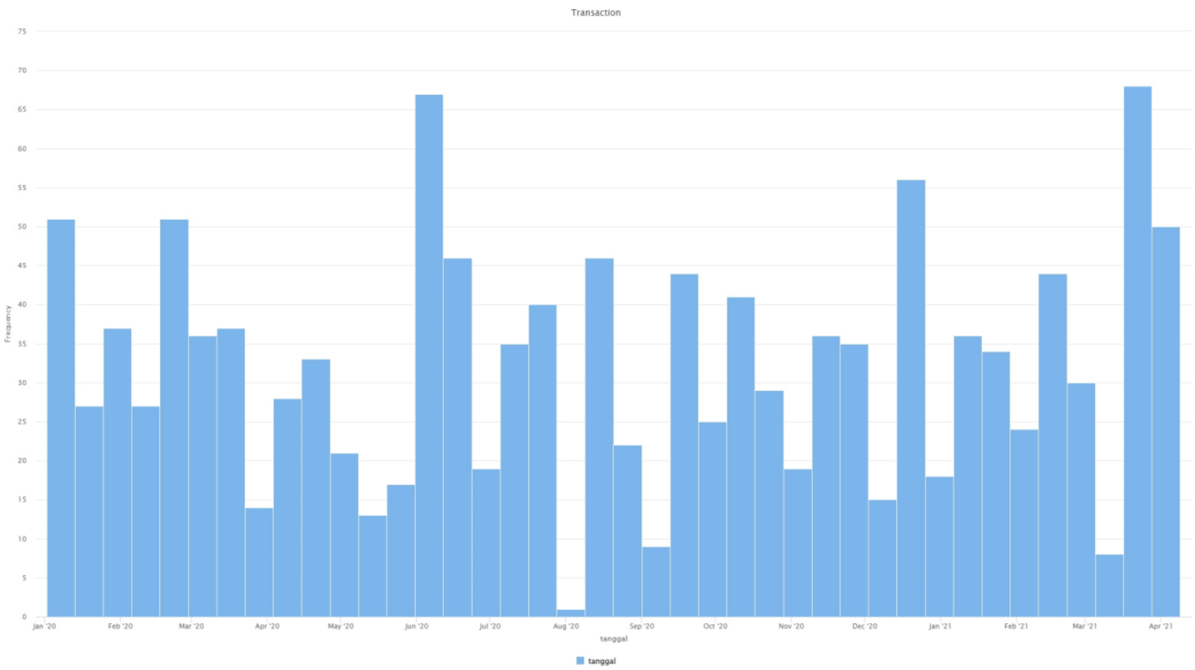

Figure 2 Transaction History

The following analysis is the sales product item on a quantum base. The bar graph shows the frequency distribution of 5 types of goods. Rice (Beras) ranked first, with 836 sold followed by Meat (Daging) as many as 184, Sugar (Gula) 121, Flour (Tepung) 77, and Cooking oil or MIGOR (Minyak Goreng) 71, which are in the last position. From this result, the total quantum of the five goods is 1284. Figure 3 is a graph that presents sales information.

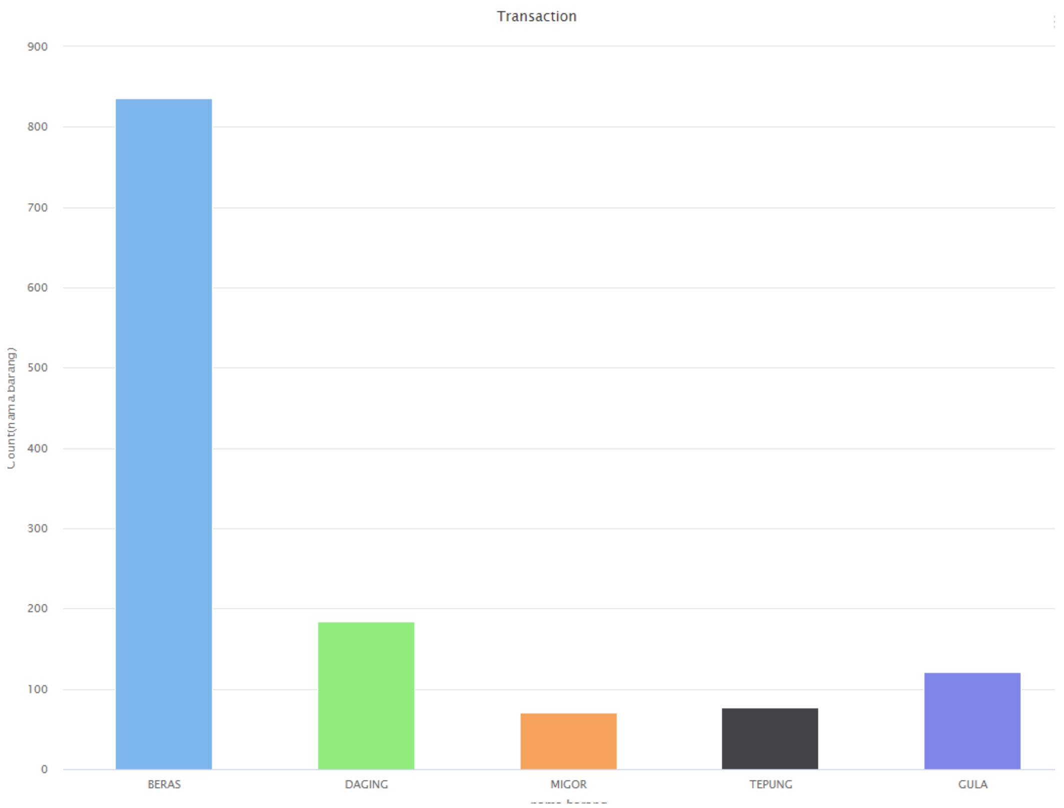

Figure 3 Sales Product Item

C. Data Preparation

Before data can be processed using the ARIMA model, it is necessary to prepare data first. This is because the ARIMA model has several basic assumptions that must be met. First, ARIMA assumes that the data is stationary, meaning that mean, variance and covariance characteristics do not change over time. Data with duplicate dates often violate this assumption because values on the same date can be very different, making it difficult to identify consistent patterns. Second, ARIMA requires that each data point has a unique timestamp. Data with duplicate dates confuses the model because it can't determine the exact sequence of events. Third, ARIMA also assumes that observations at different times are independent. If there are multiple observations on the same date, this assumption is violated, and the model cannot capture the proper relationship between those observations. Therefore, to meet the assumptions of ARIMA, the date will be changed from a date format to a numeric format. Thus, the data that initially contained the period from January 2020 to April 2021 will be changed to a numerical value from 601 to 616.

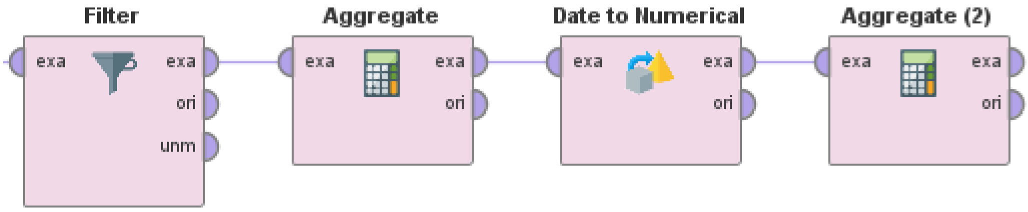

Figure 4 Operators in data preparation

Figure 4 shows the data preparation process for the ARIMA model in RapidMiner, consisting of 4 main steps:

1) Select the relevant columns and items to be subject to ARIMA operations
2) Aggregate to combine data by date
3) Date to Numerical to change the date format to numeric,
4) Aggregate (2) to ensure no duplicate data is based on the numerical value in the date column. This additional Aggregate stage is important to maintain the time series model's accuracy and meet the data stationarity assumption.

Table 1 shows the results of the Preparation data process using sales data for BERAS items. It presents rice sales data that has been processed and reformatted according to the needs of the ARIMA model.

Table 1. Data Preparation Results

No.	Item Name	Date	Quantum
1	BERAS	601	127040
2	BERAS	602	223734
3	BERAS	603	152110
4	BERAS	604	67130
5	BERAS	605	250000
6	BERAS	606	117496
7	BERAS	607	169916
8	BERAS	608	143987
9	BERAS	609	97916
10	BERAS	610	74189
11	BERAS	611	187765
12	BERAS	612	137945
13	BERAS	613	36600
14	BERAS	614	93800
15	BERAS	615	6660
16	BERAS	616	78970

D. Forecasting

The forecasting process uses two main methods: ARIMA and Exponential Smoothing. In the Apply Forecast section for ARIMA, a forecast horizon concept regulates the number of periods in the future to be predicted. The use of these two methods is shown in rapidminer operators, as shown in Figure 5

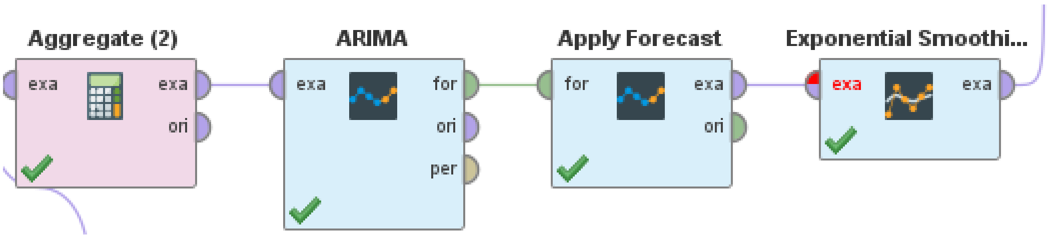

Figure 5. ARIMA and Exponential Smoothing Operators

In this case, the forecast horizon value is set to 3, meaning that the ARIMA model will provide a prediction for the next 3 months. As a result, the date column, which initially had 16 rows, changed to 19. Meanwhile, in the Exponential Smoothing section, an alpha parameter regulates the weight given to the latest data vs historical data. In this diagram, the alpha value is set to 0.5, meaning that the most recent and historical data are given equal weight. The results of ARIMA and Exponential Smoothing Forecasting are shown in Table 2.

Table 2. ARIMA Forecasting and Exponential Smoothing

Date	ARIMA	Exponential Smoothing
601	127040	127040
602	223734	175387
603	152110	163748.500
604	67130	115439.250
605	250000	182719.625
606	117496	150107.813
607	169916	160011.906
608	143987	151999.453
609	97916	124957.727
610	74189	99573.363
611	187765	143669.182
612	137945	140807.091
613	36600	88703.545
614	93800	91251.773
615	6660	48955.886
616	78970	63962.943
617	120708.745	92335.844
618	122726.162	107531.003
619	122823.673	115177.338

E. Evaluation

The forecasting results carried out previously will be measured for accuracy using MAPE. MAPE is a statistical measure used to evaluate the accuracy of Exponential Smoothing forecasting against the forecasting carried out by ARIMA, which provides predictions for the next 3 months. MAPE is measured from the first month to the 19th month and includes forecasting. The results of the MAPE measurement show a figure of 23.646%, which means that the accuracy of this model is quite good.

3.2 Discussion

This study tries to present the application of predictive analysis to forecast sales transaction data for the next month. Here is the graph data of the five types of merchandise analyzed using the ARIMA and Exponential Smoothing algorithms. The analysis results are presented in the form of graphs and tables to provide a more comprehensive picture of each product's sales patterns and trends.

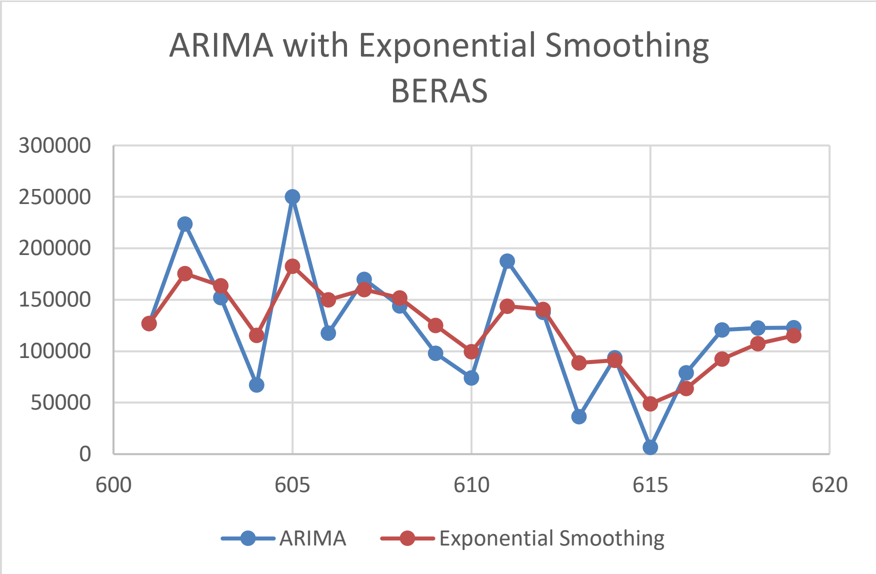

Figure 6. Rice Forecasting Results

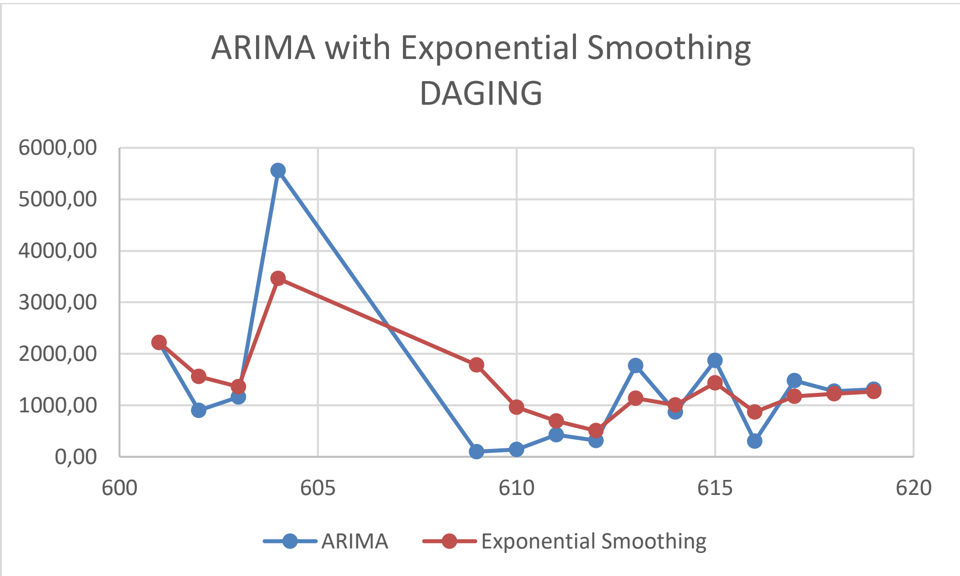

Figure 7. Meat Forecasting Results

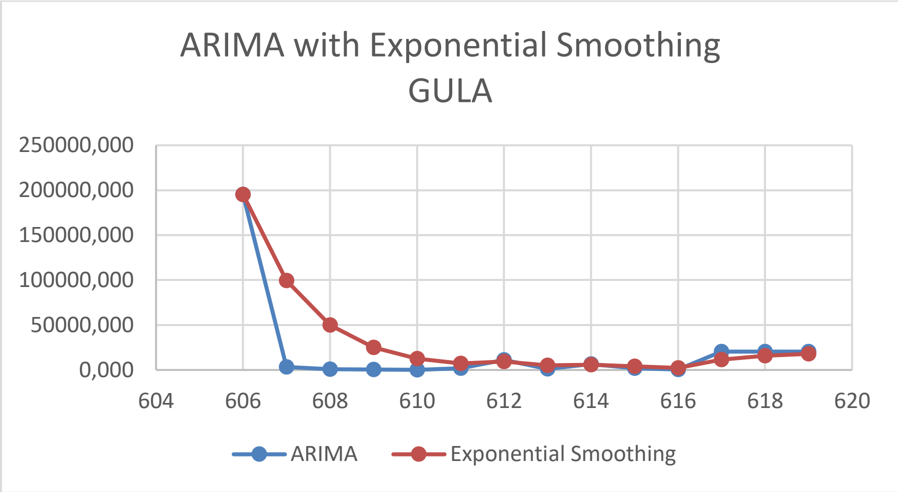

Figure 8. Sugar Forecasting Results

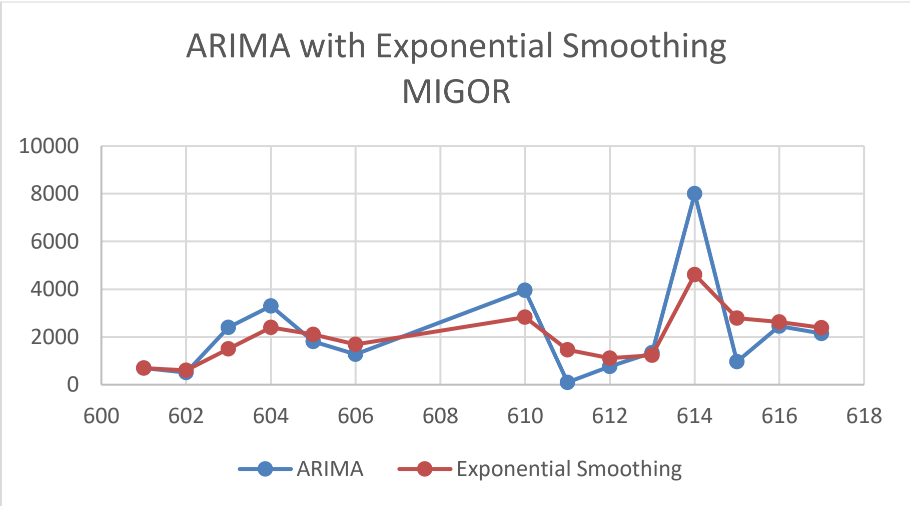

Figure 9. MIGOR Forecast Results

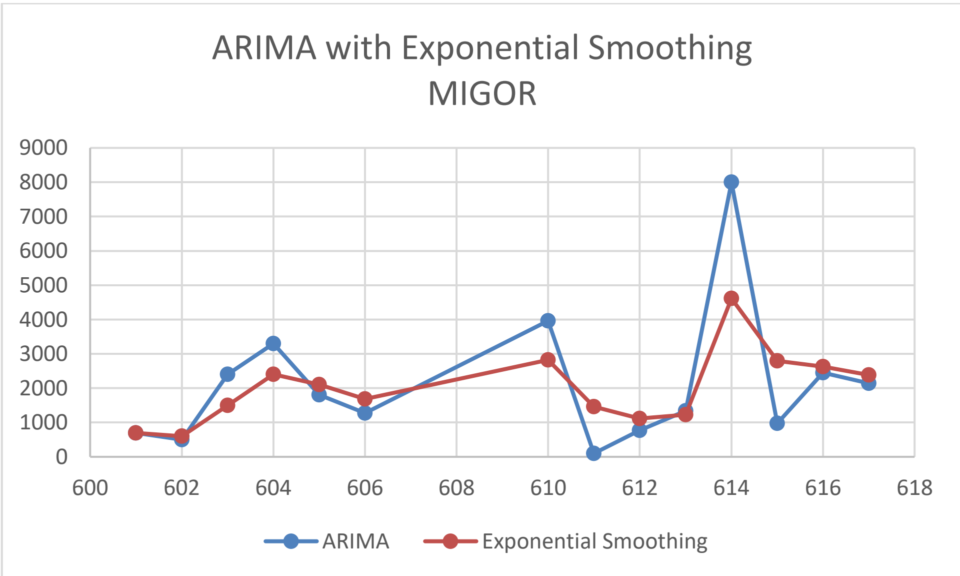

Figure 10. Flour Forecasting Results

The graph presented shows that some types of merchandise do not experience sales activity in certain months. This can affect forecasting results, as analytical models cannot capture unstable or consistent sales patterns for those products. Fluctuations and instability in sales data can make it difficult for predictive models to produce accurate forecasts.

Table 3. MAPE Accuracy Rating

Item Name	MAPE
BERAS	23.646
DAGING	38.080
GULA	58.509
MIGOR	34.378
TEPUNG	26.553

From the observation results in Table 3, the ARIMA and Exponential Smoothing models have shown relatively good accuracy with a MAPE value of 23.646% on rice (beras) trade. All merchandise shows quite good results, but the accuracy value reaches 58.509% in sugar (gula) items. This is because sugar sales data shows higher fluctuations and is unstable, making it more difficult for predictive models to produce accurate forecasts. Economic conditions, consumer trends, and market competition can affect sugar sales patterns and cause difficulties in modelling. This indicates that these models can be used to forecast future sales patterns and trends with an adequate level of reliability.

The results of this research can provide valuable insights for management in developing more effective business plans and strategies to deal with market dynamics. Furthermore, further research can explore the potential for improved model accuracy by considering other factors that affect sales, such as economic conditions, consumer trends, and market competition.

4. Conclusion

This study aims to present the application of predictive analysis in developing a sales forecasting model for the coming months. The analysis results are presented in graphs and tables to provide a more comprehensive overview of the sales patterns and trends of each product analyzed. The findings of this study can provide valuable insights for management in developing more effective business plans and strategies to deal with market dynamics. Further studies can be conducted to explore improving the model's accuracy by considering other factors that affect sales, such as economic conditions, consumer trends, and market competition.

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