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Exploration of the Evolution of SISGANIS: Analytical Intelligence Approach in Raw Material Inventory Management and Interactive Visual Analysis Cafe Rengganis

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ABSTRACT

SISGANIS (Rengganis Management Information System), developed in 2023 by the ITS Mandala Jember team and granted intellectual property rights (EC002023118017), focuses on automating raw material stock balances and financial reporting. Despite its active use by Cafe Rengganis in Jember Regency, it remains a Basic Information System, concentrating primarily on transaction data. Consequently, it lacks accurate real-time inventory forecasts and interactive visual analyses. The research is driven by Cafe Rengganis's need to enhance raw material inventory management efficiency. Frequent issues with determining appropriate stock levels lead to stockouts and inaccurate records. This necessitates exploring an advanced SISGANIS for more effective operations. The research utilizes Exponential Smoothing, Decomposition Methods, and Machine Learning (ML)-based data transformation to improve historical data processing, identifying complex patterns and trends in inventory management. Adopting an AGILE approach, the research team comprising IT experts, accountants, and students ensures rapid response and continuous iteration. The goal is to successfully implement the new SISGANIS version, enhancing inventory management efficiency, predicting raw material needs, and providing interactive data visualization tools, ultimately optimizing Cafe Rengganis's operational performance and customer experience.

Keywords : Forecasting, Exponential Smoothing, Decomposition Methods, Interactive Visual Analysis, Raw Material Inventory

1. INTRODUCTION

Effective management of raw material inventory is crucial for maintaining the operational efficiency of businesses, especially in the food and beverage industry. Cafe Rengganis, located in Jember Regency, has been utilizing the **SISGANIS (Rengganis Management Information System)** developed by the ITS Mandala Jember team since 2023. SISGANIS, which has received intellectual property rights (**EC002023118017**), aims to automate the calculation of raw material stock balances and streamline financial reporting processes. Despite its active implementation, SISGANIS is still classified as a Basic Information System, primarily focusing on transaction data without providing accurate real-time inventory forecasts or interactive visual analysis.
This limitation has led to significant challenges for Cafe Rengganis. The inability to determine appropriate stock levels often results in stockouts and inaccurate record-keeping, thereby affecting the cafe's overall operational efficiency (Soeseno et al., 2023) (Kavya B et al., 2022). The need for an

advanced and informative evolution of SISGANIS is apparent to address these issues and enhance the management of raw material inventory.

The proposed research seeks to upgrade SISGANIS by integrating sophisticated forecasting techniques, including Exponential Smoothing and Decomposition Methods, along with Machine Learning (ML)-based data transformation (Fachrurrazi, 2023) (Maricar, 2019; Rachman, 2018; Xie et al., 2020). These methods are expected to improve the processing of historical data, enabling the identification of complex patterns and trends in inventory management (Adriel Silaen & Iskandar, 2023; Lim & Zohren, 2021; Peng et al., 2023). Furthermore, the adoption of an AGILE approach ensures rapid response to changes and continuous iteration, thereby aligning the system development with the dynamic needs of Cafe Rengganis.

The objective of this research is to implement a new version of SISGANIS that not only enhances the efficiency of raw material inventory management but also provides accurate predictions of inventory needs and interactive data visualization tools. By achieving these goals, Cafe Rengganis can optimize its operational performance, minimize stockouts, and deliver a better customer experience. The successful implementation of the new SISGANIS is also anticipated to contribute to academic knowledge through publications in accredited journals.

Inventory Management Systems

Inventory management systems are essential for maintaining optimal stock levels and preventing both overstock and stockouts (J. Li et al., 2021; Rushton et al., 2023). Traditional systems often rely on manual record-keeping, which can lead to inaccuracies and inefficiencies. Advanced inventory management systems incorporate automated processes and data analytics to provide real-time insights and improve decision-making (Tao et al., 2018).

Exponential Smoothing Methods

Exponential Smoothing is a time series forecasting technique that applies weighted averages to past observations, giving more weight to recent observations. This method is effective in capturing trends and patterns in historical data, making it a popular choice for inventory forecasting. introduced the concept, and it has since been widely adopted in various industries for its simplicity and effectiveness in short-term forecasting (Rezai, 2024; Woo et al., 2022). The general formula for Exponential Smoothing is:

$$\boldsymbol{S_t = \alpha X_t + (1 - \alpha) S_t - 1}$$

where:

$\boldsymbol{S_t}$ is the smoothed statistic for time period $\boldsymbol{t}$,
$\boldsymbol{\alpha}$ is the smoothing constant **(0 < $\boldsymbol{\alpha}$ < 1)**,
$\boldsymbol{X_t}$ is the actual value at time $\boldsymbol{t}$,
$\boldsymbol{S_t - 1}$ is the previous smoothed statistic.

Decomposition Methods

Decomposition methods involve breaking down time series data into trend, seasonal, and irregular components. This approach allows for a better understanding of the underlying patterns in the data and improves the accuracy of forecasts. The classic decomposition method involves additive or multiplicative models, which have been extensively used in forecasting applications(Mahajan et al., 2018; MD ROKIOBUL HASAN, 2024; Wu et al., 2021; Zhou et al., 2022). The general additive decomposition model can be expressed as:

$$\boldsymbol{Y_t = T_t + S_t + I_t}$$

where:

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Y_t is the observed value at time t,
T_t is the trend component,
S_t is the seasonal component,
I_t is the residual component.

The multiplicative model can be expressed as:

$$Y_t = T_t \times S_t \times I_t$$

These models have been extensively used in forecasting applications (Makridakis, Wheelwright, & Hyndman, 1998).

Machine Learning in Inventory Management

Machine Learning (ML) techniques have revolutionized inventory management by enabling the analysis of large datasets to uncover complex patterns and trends (Jiang et al., 2020; D. Li et al., 2022). Algorithms such as decision trees, neural networks, and support vector machines have been applied to predict inventory needs accurately. ML-based systems can adapt to changing conditions and provide more accurate forecasts compared to traditional methods (Woo et al., 2022).

Data Transformation Methods

Data transformation is crucial for improving the performance of machine learning models. Data transformation is performed to address the frequent inaccuracies in sales transaction data, which often result from some transactions still being recorded manually (Hodson, 2022). This transformation aims to ensure better data quality, thereby making forecasting more accurate. Four primary data transformation methods are utilized in this research: standardization, normalization, log transformation, and square root transformation.

Standardization, also known as Z-score normalization, converts data so that it has a mean of zero and a standard deviation of one. This method is particularly useful when dealing with data that has various scales and units, allowing forecasting algorithms to work more efficiently with homogenized data. Normalization, on the other hand, scales data to the range of [0, 1]. This technique addresses the issue of differing scales and prevents extreme values from disproportionately influencing forecasting results, especially when dealing with data that spans a wide range.

Log transformation is employed to reduce skewness in non-normal data distributions. It is particularly effective for handling data with log-normal distributions or significant outliers, thereby clarifying trend patterns and enhancing prediction accuracy. Lastly, square root transformation is an effective method for reducing skewness in Poisson-distributed data. It is often applied to data with variance proportional to the mean, aiding in variance stabilization and making the data more suitable for advanced statistical analysis. By implementing these transformation techniques, the research ensures the improved quality of sales transaction data, leading to more precise and reliable forecasting outcomes.

Four common data transformation techniques are used in this research:

1. Standardization: Adjusts the data to have a mean of zero and a standard deviation of one (Adlam et al., 2020).

   $$Z = \frac{X - \mu}{\alpha}$$

   where:

   Z is the standardized value,
   X is the original value,
   μ is the mean of the data,

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$\boldsymbol{\alpha}$ is the standard deviation of the data

2. Normalization: Scales the data to a fixed range, typically 0 to 1, which can improve the convergence speed of many machine learning algorithms (Patro & sahu, 2015; Peterson, 2021).

$$\boldsymbol{X'} = \frac{\boldsymbol{X} - \boldsymbol{X_{min}}}{\boldsymbol{X_{max}} - \boldsymbol{X_{min}}}$$

where:

$\boldsymbol{X'}$ is the normalized value,
$\boldsymbol{X}$ is the original value,
$\boldsymbol{X_{min}}$ is the minimum value in the data,
$\boldsymbol{X_{max}}$ is the maximum value in the data.

3. Log Transformation: Reduces skewness by applying the natural logarithm to the data, which is particularly useful for data with exponential growth patterns.

$$\boldsymbol{X'} = \boldsymbol{log}(\boldsymbol{X})$$

where:

$\boldsymbol{X'}$ is the log-transformed value,
$\boldsymbol{X}$ is the original value.

4. Square Root Transformation**:** Reduces the impact of large values and normalizes the distribution of the data.

$$\boldsymbol{X'} = \sqrt{\boldsymbol{X}}$$

where:

$\boldsymbol{X'}$ is the square root-transformed value,
$\boldsymbol{X}$ is the original value.

These transformations help in processing historical data related to raw material inventory, allowing the identification of more complex patterns and trends.

Integration of Exponential Smoothing with Decomposition

Combining Exponential Smoothing with decomposition methods allows for a more nuanced forecasting approach by integrating decomposed components into the smoothing process . This integration enhances the accuracy of forecasts by accounting for the underlying patterns in the data. The integrated formula for Exponential Smoothing with decomposition can be expressed as (Adlam et al., 2020; Dudek & Smyl, 2022) (Adlam et al., 2020)(Yang et al., 2015):

$$\mathbf{forecast}_{\boldsymbol{t}} = \boldsymbol{e}.\boldsymbol{\alpha}(\boldsymbol{T_t} + \boldsymbol{S_t} + \boldsymbol{I_t}) + (\mathbf{1} - \mathbf{e}.\boldsymbol{\alpha}) \cdot \boldsymbol{F}_{\mathbf{t-1}}$$

where:

$\mathbf{forecast}_{\boldsymbol{t}}$ is the forecast value for period $\boldsymbol{t}$,
$\boldsymbol{e}.\boldsymbol{\alpha}$ is the smoothing constant,
$\boldsymbol{T_t}$ is the trend component at period $\boldsymbol{t}$,
$\boldsymbol{S_t}$ is the seasonal component at period $\boldsymbol{t}$,
$\boldsymbol{I_t}$ is the residual component at period $\boldsymbol{t}$,

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F_{t-1} is the forecast value from the previous period.

Explanation

Decomposition Components

T_t = Trend Component
S_t = Seasonal Component
I_t = Residual Component

Exponential Smoothing

$e.\alpha$ = Smoothing Constant ($0 < e.\alpha < 1$)
$(1 - e.\alpha)$ = Weight for the previous forecast

This formula combines the decomposed trend, seasonal, and residual components with the Exponential Smoothing method to produce a more accurate forecast. This approach accounts for both the historical decomposed information and recent trends.

AGILE Methodology

The AGILE methodology is an iterative approach to software development that emphasizes flexibility, collaboration, and customer feedback. AGILE allows for continuous improvement and rapid adaptation to changing requirements, making it particularly suitable for projects where needs evolve over time. The methodology consists of short development cycles called sprints, during which specific features are developed, tested, and reviewed (Varl et al., 2020).

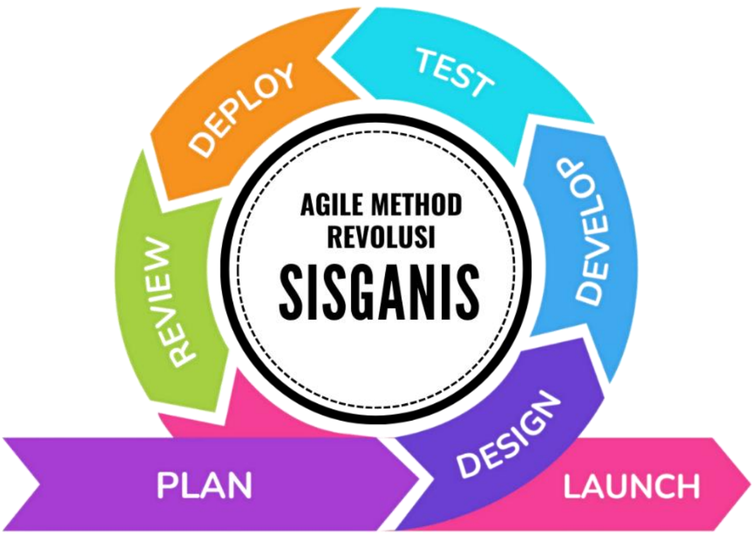

Figure 1. Agile Method Revolusi SISGANIS

Interactive Data Visualization

Interactive data visualization tools enhance the ability to analyze and interpret complex datasets by providing intuitive graphical representations. These tools enable users to explore data dynamically,

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identify trends, and make informed decisions. The use of interactive visualizations in inventory management systems helps stakeholders understand inventory levels, forecast accuracy, and other key performance indicators.

Applications in the Food and Beverage Industry

Inventory management in the food and beverage industry presents unique challenges due to the perishable nature of products and the need for precise stock control. Studies have shown that advanced inventory management systems incorporating forecasting techniques and interactive visualizations can significantly improve operational efficiency in this sector.

SISGANIS and Its Evolution

SISGANIS, developed by the ITS Mandala Jember team, aims to address the specific needs of Cafe Rengganis by automating inventory management and financial reporting. Despite its initial success, the system's limitations in real-time forecasting and interactive visual analysis have highlighted the need for further development. Integrating advanced forecasting methods and ML-based data transformation can enhance SISGANIS's capabilities, making it a more robust tool for managing raw material inventory.

By reviewing the literature on inventory management systems, forecasting methods, machine learning applications, data transformation techniques, AGILE methodology, and interactive data visualization, this study aims to provide a comprehensive framework for the evolution of SISGANIS. The integration of these advanced techniques is expected to address the current system's limitations and improve the overall efficiency and effectiveness of inventory management at Cafe Rengganis.

2. RESEARCH METHOD

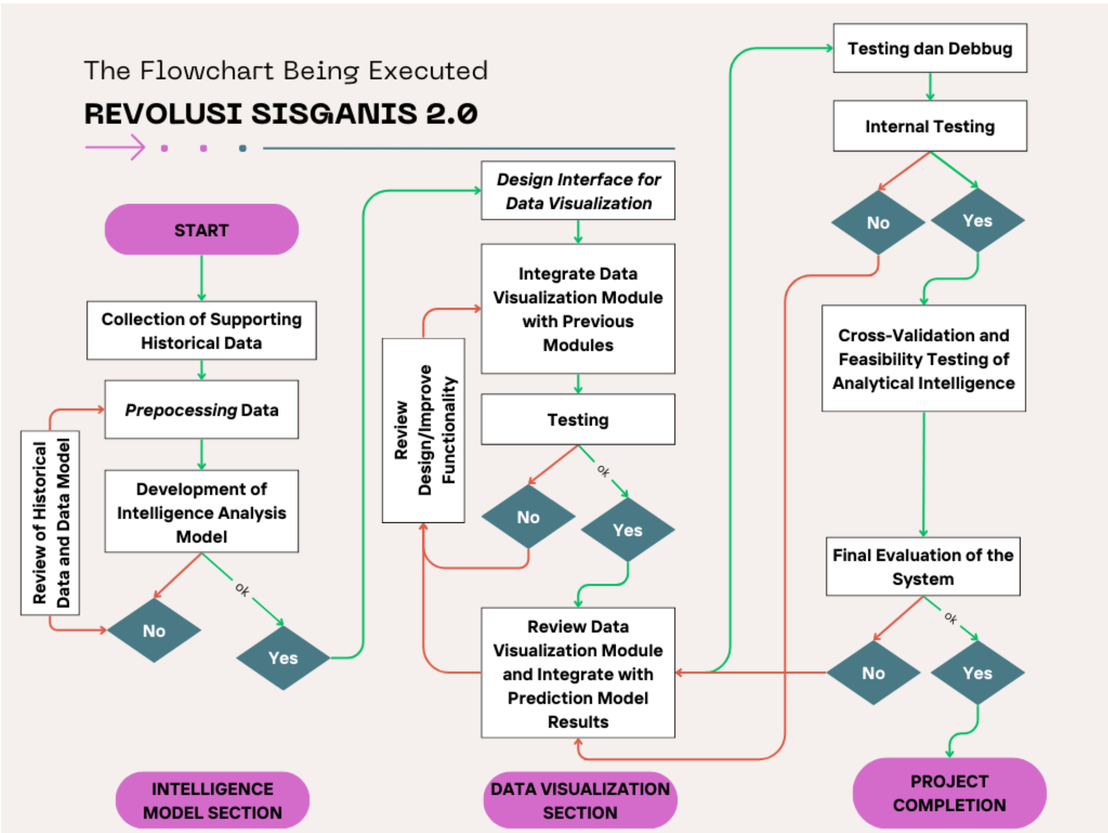

Figure 2. Flowchart Being Executed

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The flowchart titled "The Flowchart Being Executed REVOLUSI SISGANIS 2.0" outlines a structured process for developing and implementing an intelligence analysis model with integrated data visualization components. The process begins with the collection and preprocessing of supporting historical data, followed by the development of the intelligence analysis model. This model is then reviewed to ensure accuracy. Once validated, the process moves to the design of the data visualization interface, which is subsequently integrated with the existing modules. The integrated system undergoes rigorous testing, followed by a review and improvement phase to refine its design and functionality.

The data visualization module is further reviewed and integrated with the prediction model results, leading to additional testing. In the final stages, the system undergoes extensive testing and debugging, including internal testing and cross-validation to ensure the feasibility and accuracy of the analytical intelligence. The project concludes with a final evaluation of the entire system to confirm it meets all requirements and standards. This iterative process ensures the development of a robust and effective intelligence analysis model complemented by interactive data visualization tools.

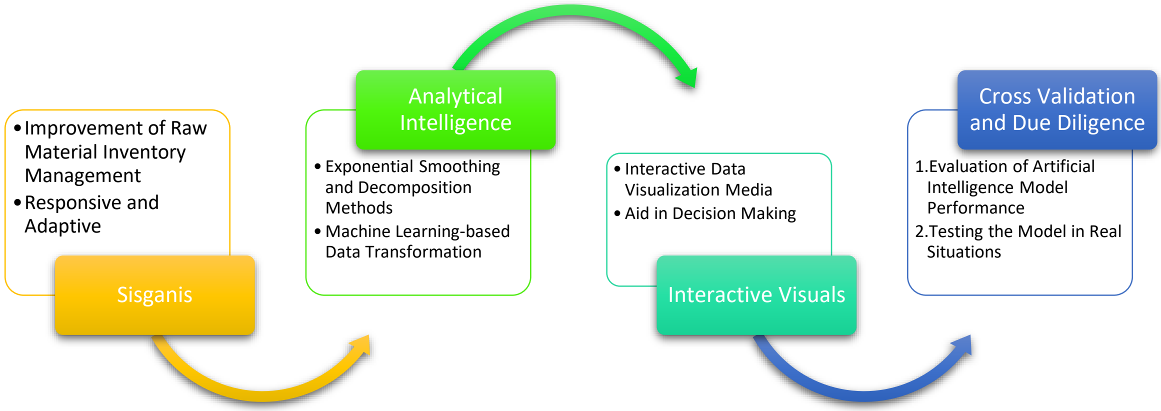

Figure 3. Diagram Outlines

The diagram outlines a streamlined process for improving raw material inventory management through the integration of analytical intelligence and interactive visualization tools, followed by validation and feasibility testing. The process begins with the enhancement of raw material inventory management, focusing on making the system more responsive and adaptive. This is achieved through the application of advanced analytical intelligence techniques, including Exponential Smoothing and Decomposition Methods, and Machine Learning-based Data Transformation. These techniques help in accurately forecasting and managing inventory levels, thereby optimizing resource utilization.

Next, interactive data visualization media are employed to aid in decision-making. These visualization tools present complex data in an accessible and intuitive format, enabling stakeholders to make informed decisions quickly. The final phase involves the cross-validation and feasibility testing of the artificial intelligence model. This includes evaluating the model's performance and testing it in real-world scenarios to ensure its effectiveness and reliability. The process ensures that the implemented system is robust, efficient, and capable of meeting the dynamic needs of inventory management.

3. RESULTS AND DISCUSSION

This research explores the evolution of SISGANIS through an analytical intelligence approach in raw material inventory management and interactive visual analysis at Cafe Rengganis. The SQL code used in this research aims to model the forecasting of raw material usage using the exponential smoothing method. The process begins by selecting historical raw material usage data from the exponential_smoothing table and calculating future usage estimates (forecast) based on trend, seasonal, and residual components. This data is then combined to produce updated daily forecasts, considering the alpha value for data smoothing.

Evolusi SISGANIS

SISGANIS has undergone significant development since its implementation at Cafe Rengganis. The initial version, which only covered basic inventory management of raw materials, has now evolved

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into an advanced analytical tool with an analytical intelligence approach. These changes include improvements in several key aspects. Based on its latest version development, SISGANIS has experienced significant advancement by integrating data from various sources, including information related to raw material usage and sales data. This integration enables the system to provide a more holistic view of inventory and raw material needs, thus facilitating more efficient management. Additionally, SISGANIS is now equipped with more advanced analytical capabilities. With the application of modern analytical techniques, the system can analyze patterns in raw material consumption and predict future needs based on historical trends, which supports more accurate planning and waste reduction. One of the major innovations introduced is the interactive visualization feature. The charts and dashboards produced by this feature allow users to understand data more intuitively and make more informed decisions based on the displayed information. The following final images show some screenshots of the SISGANIS system that has been successfully developed.

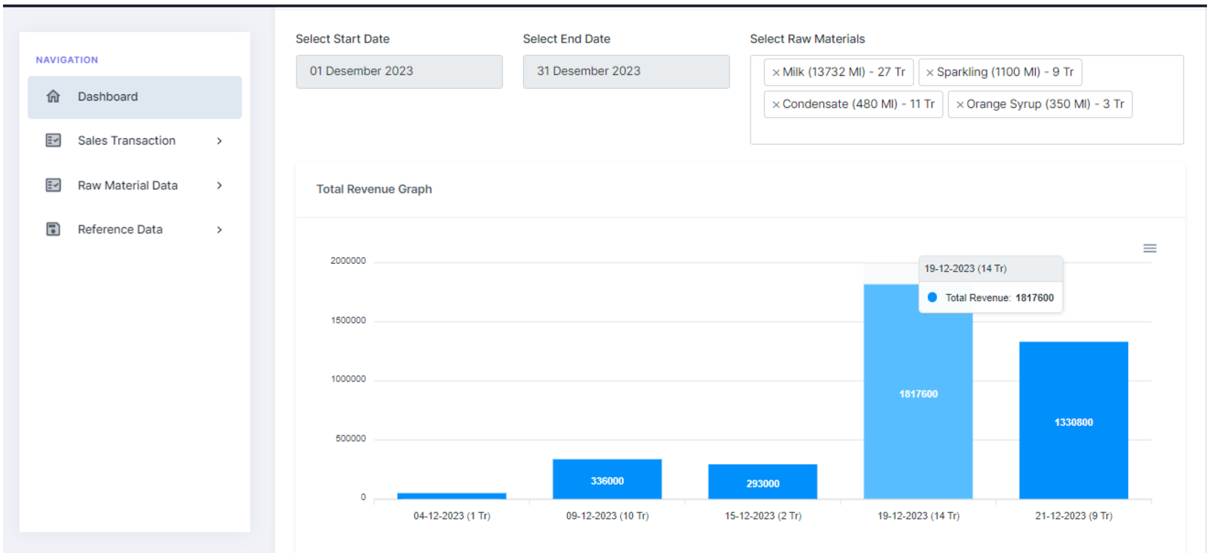

Figure 4. Custom analysis visualization of revenue forecasting conditions, raw material usage recap, and product sales recap.

Based on Figure 4, the management of Cafe Rengganis can easily monitor the cafe's revenue in real-time. This visualization feature significantly simplifies cafe management by enabling direct monitoring of revenue conditions. The presence of this tool provides substantial benefits to the management, as they can quickly access and analyze revenue data for more accurate and responsive decision-making in response to changes.

Based on Figure 5, the cafe management can monitor raw material usage on a daily basis and filter data according to specific periods and select which type of raw material to analyze, taking into account the unit type of each raw material in real-time. This feature enables accurate and up-to-date monitoring of raw material consumption, allowing management to make necessary adjustments to optimize inventory management and reduce waste.

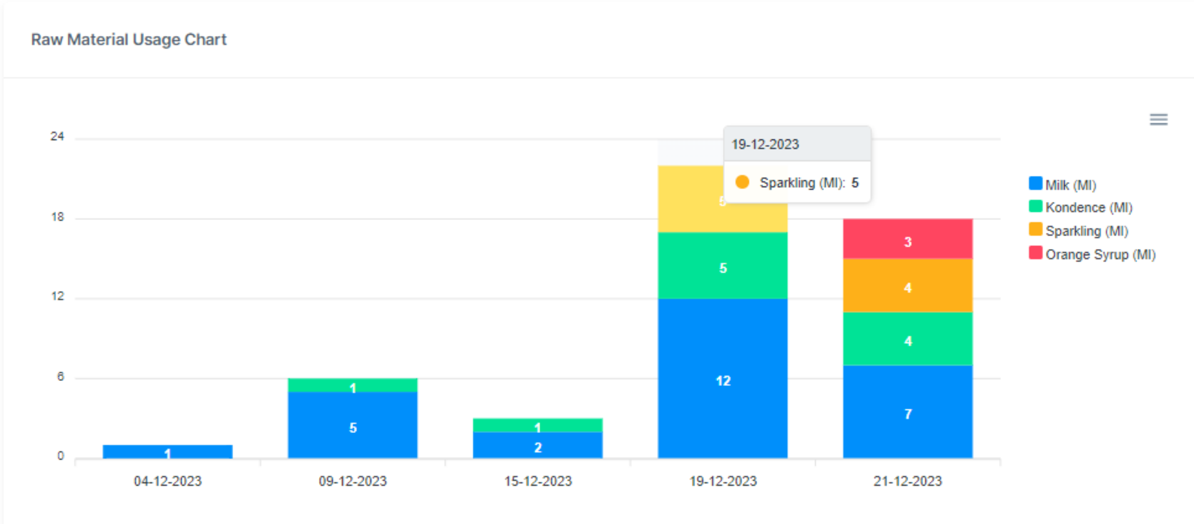

Figure 5 Raw Material Usage Chart

Based on Figure 5, the cafe management can monitor raw material usage on a daily basis similarly to Figure 4, except that in this section all used raw materials are visible.

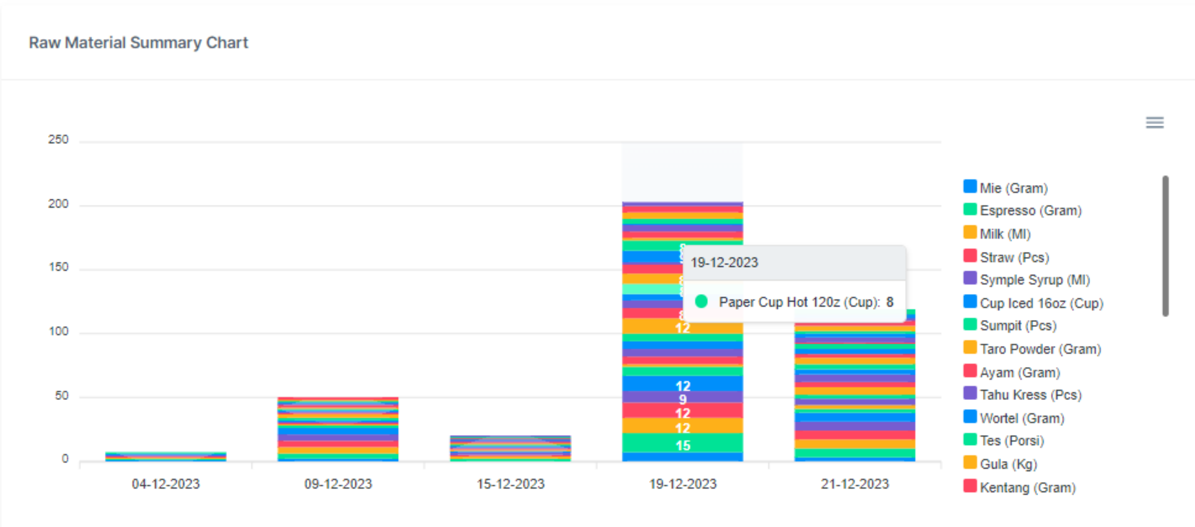

Figure 6. Raw Material Summary Chart

Based on Figure 7, the management of Cafe Rengganis can monitor product sales in detail, including information about the most frequently sold products. This feature provides management with deep insights into sales patterns, which significantly aids in managing sales strategies and product stock. This information allows management to identify the most popular products and adjust marketing and inventory decisions more effectively.

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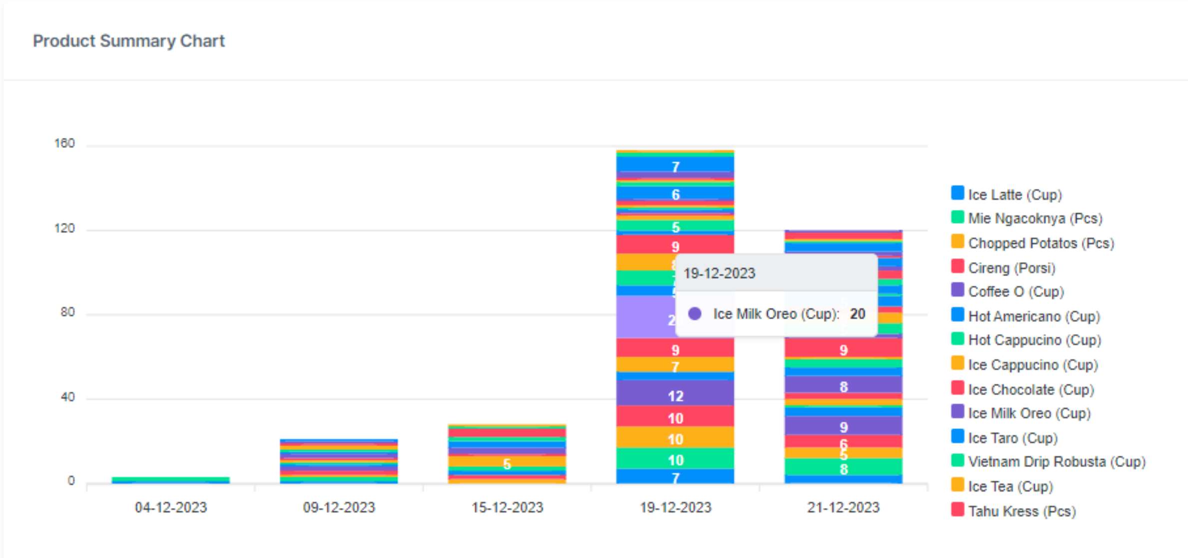

Figure 7. Product Summary Chart

Based on Figure 8, the cafe management can monitor revenue based on each shift or employee working hours. This feature enables more effective management by providing real-time information on revenue generated during specific working hours. With this data, management can ensure that the cafe's revenue aligns with employee working hours, and make evaluations and adjustments as needed to improve operational efficiency and financial performance.

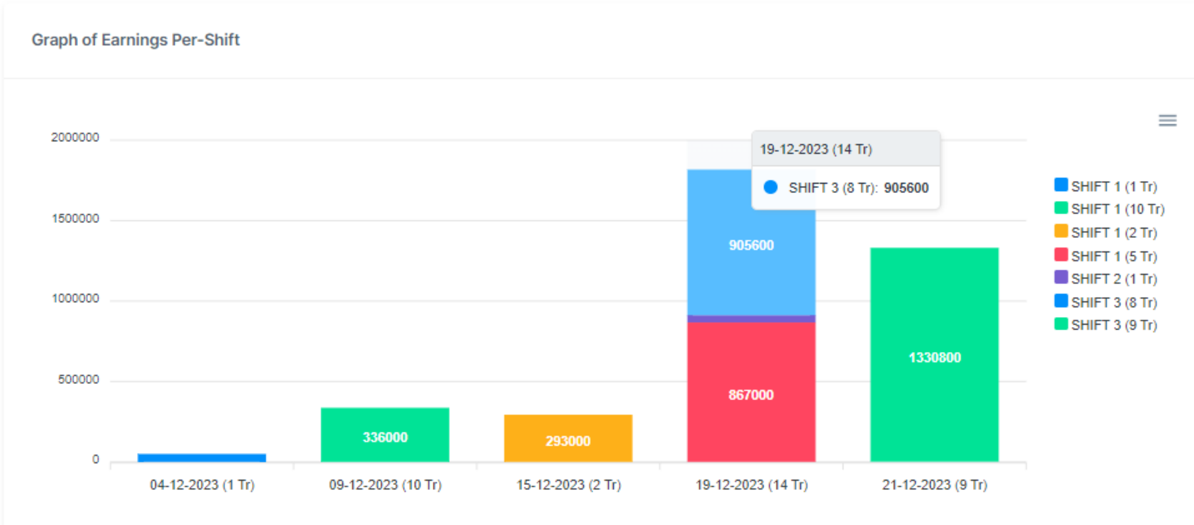

Figure 8. Earning per Shihft

Furthermore, the research calculates the forecast error (Mean Squared Error or MSE) in percentage form to evaluate the accuracy of the forecasting model used. These calculations indicate how closely the estimated raw material usage aligns with actual usage at Cafe Rengganis. By employing this analytical intelligence approach, Cafe Rengganis is expected to manage raw material inventory more effectively and efficiently, leveraging interactive visual analysis to gain deeper insights into raw material usage patterns.

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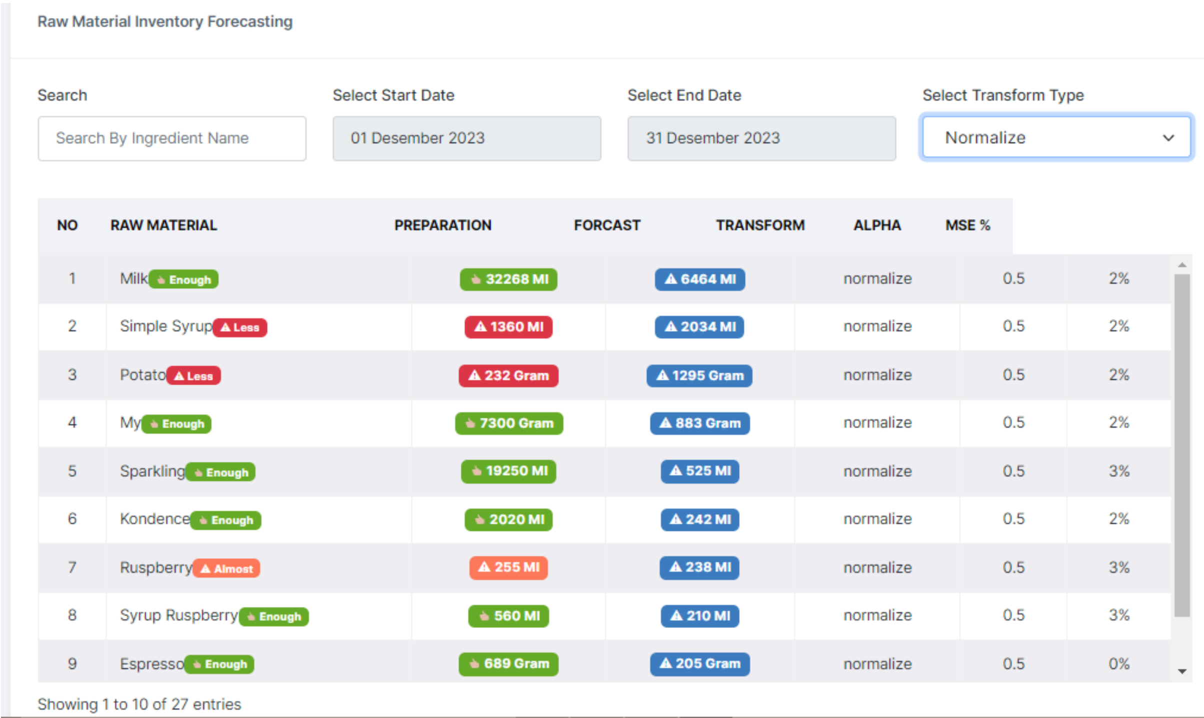

NO	RAW MATERIAL	PREPARATION	FORCAST	TRANSFORM	ALPHA	MSE %
1	Milk Enough	32268 Ml	6464 Ml	normalize	0.5	2%
2	Simple Syrup Less	1360 Ml	2034 Ml	normalize	0.5	2%
3	Potato Less	232 Gram	1295 Gram	normalize	0.5	2%
4	My Enough	7300 Gram	883 Gram	normalize	0.5	2%
5	Sparkling Enough	19250 Ml	525 Ml	normalize	0.5	3%
6	Kondence Enough	2020 Ml	242 Ml	normalize	0.5	2%
7	Ruspberry Almost	255 Ml	238 Ml	normalize	0.5	3%
8	Syrup Ruspberry Enough	560 Ml	210 Ml	normalize	0.5	3%
9	Espresso Enough	689 Gram	205 Gram	normalize	0.5	0%

Figure 9. Table of raw material usage forecasting

Based on Figure 9, we can see the forecast results for raw material needs at Cafe Rengganis, including various components such as current inventory, forecasted needs, and data transformation results. This table is designed to provide in-depth insights into inventory status and raw material requirements projections, as well as the accuracy of the forecasting model used.

1. The "No" column lists the sequential number for referencing each raw material..
2. The "Raw Material" column specifies the type of raw material in question.
3. The "Inventory" column shows the current inventory status with visual indicators representing raw material availability (👍 **Enough,** ⚠️ **Less, and** ⚠️ **Almost**).
4. The "Forecast" column presents the amount of raw material projected to be needed based on the forecasting model, including the unit of measurement. This column also includes visual indicators providing information on raw material adequacy.

   To generate accurate forecast values, the system is developed based on existing historical sales data. The process begins with data analysis using machine learning techniques to assess the quality of available data. The data used is daily data, which forms the basis for forecast value calculations. If the analysis indicates that data quality is insufficient, data transformation is performed according to the type of transformation listed in the "Transform" column to improve the forecasting input quality.

   After data transformation, if needed, the forecasting model is then applied using decomposition techniques and exponential methods. Decomposition breaks the data into trend, seasonal, and residual components, while the exponential method gives more weight to the most recent data to produce more relevant projections. The final result is a forecast value indicating future raw material needs, designed to help cafe management plan inventory more effectively and avoid shortages that could impact cafe operations.
5. The "Transform" column shows the data transformation method used, in this case, "normalize" with the best alpha parameter value of 0.5.
6. The "Alpha" column lists the smoothing parameter value, which in this case is 0.5, representing the best alpha value applied in forecasting. This forecasting system has automatically determined the optimal alpha value within the range of 0 to 1 using an exhaustive search

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technique. This process involves testing various possible alpha values to find the one that provides the best results in terms of prediction accuracy. Specifically, the system considers the smallest MSE (Mean Squared Error) value as the primary metric for selecting the most suitable alpha value. With this approach, the system minimizes forecasting errors and ensures that the model provides the most accurate projections for raw material needs, thus helping cafe management make better, data-driven decisions.

7. The "MSE %" column illustrates the percentage of Mean Squared Error, indicating the forecasting model's accuracy level.

Based on some results from this table, some raw materials show adequate inventory status, such as Milk, Noodles, and Espresso, where the forecasted needs remain within manageable limits. Conversely, raw materials like Simple Syrup, Potatoes, and Raspberry show "Less" or "Almost" status, with forecasted needs significantly higher than current inventory. This indicates a shortage of raw materials that need to be addressed promptly to avoid operational disruptions. The forecasting applied using normalization with an alpha parameter of 0.5 results in an MSE % ranging from 0% to 3%, showing a reasonably good model accuracy in predicting raw material needs. Low forecasting errors for raw materials like Espresso demonstrate the model's reliability, while other materials with higher MSE % might require adjustments in forecasting parameters or additional data to improve accuracy. Overall, this table provides essential guidance for cafe management to take appropriate actions in raw material inventory management, ensuring sufficient material availability and optimizing overall cafe operations.

Benefits for Cafe Rengganis

The implementation of SISGANIS at Cafe Rengganis has brought several significant benefits, enhancing both operational efficiency and service quality. First, the more integrated system and in-depth analytics allow for more efficient inventory management. By reducing errors in recording and managing raw materials, overall operational costs can be minimized, as shown in the related image.

Second, the interactive data visualization features of SISGANIS enable managers to quickly evaluate performance and make data-driven decisions. For example, trend graphs of raw material consumption support more timely purchasing decisions, helping management respond to needs more efficiently.

Third, by ensuring the availability of raw materials as needed, SISGANIS contributes to improved service quality and customer satisfaction. Consistent raw material availability reduces the likelihood of disruptions in daily operations, thus maintaining optimal customer service.

Challenges and Solutions

Despite the many benefits of SISGANIS, several challenges need to be addressed to ensure the system functions optimally. One major challenge is the need for staff training to fully utilize the advanced features of SISGANIS. To address this, comprehensive training sessions and detailed documentation have been provided to ensure staff can use the system effectively and efficiently.

Another challenge is the maintenance of the complex system, which requires regular upkeep and updates to maintain optimal performance. To address this issue, a structured maintenance plan has been implemented. This plan ensures that the system continues to operate well and provides maximum benefits to the cafe.

4. CONCLUSIONS

This research has successfully developed an advanced version of the Rengganis Management Information System (SISGANIS), which has been well received by users. The new system not only automates raw material stock and basic financial reporting but also provides real-time inventory forecasting and interactive visual analyses to assist decision-making.

In forecasting based on intelligent models, meticulous data preparation is essential, one aspect of which is data transformation. This is necessary because transaction data often suffers from inconsistencies, with some transactions recorded manually. Additionally, daily data collection requires specific handling to enhance accuracy. The research employed four relevant data transformation methods suitable for small and medium enterprises (SMEs), namely 1. Standardization, 2. Normalization, 3 Log Transformation and 4. Square Root Transformation.

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After data transformation, forecasting was performed using a combination of Exponential Smoothing methods and decomposition. The implementation of these methods significantly improved the processing of historical data, identified complex patterns and trends in inventory management, and produced forecasting results with a low Mean Squared Error (MSE), thus enhancing the system's accuracy.

One of the notable features of the latest SISGANIS version is its ability to allow users to select and test various data transformation types. Users can experiment with all four transformation methods—Standardization, Normalization, Log Transformation, and Square Root Transformation—according to their needs. This feature provides greater flexibility in the data analysis process, enabling users to choose the transformation method that best suits their data characteristics, and overall improves the convenience and effectiveness of data analysis. The new system also offers users flexibility in real-time monitoring of raw material stocks and allows them to view specific materials. This greatly supports more precise and efficient decision-making.

The AGILE approach adopted by the research team ensures a responsive and iterative system development process. Thus, the new version of SISGANIS not only enhances inventory management efficiency and accuracy in predicting raw material needs but also provides better interactive data visualization tools. Overall, the development of the latest version of SISGANIS successfully optimizes operational performance and customer experience at Cafe Rengganis.

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