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Implementation of a Machine Learning (ML) Decision Support System (DSS) for Inventory Management

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ABSTRACT

Inventory management requires an effective decision-making approach to reduce the risk of slow-moving and dead stock products. This research develops a Machine Learning-based Decision Support System (DSS) for inventory management at PT Global Bangunan Jaya. The proposed system integrates Random Forest for inventory classification, Linear Regression for sales prediction, and K-Means Clustering for product segmentation using historical inventory and sales data. The results show that Random Forest achieved an accuracy of 88.4% with precision, recall, and F1-score values of 0.88. Linear Regression obtained an R^2 value of 0.681, while K-Means successfully generated three inventory clusters with a Silhouette Score of 0.336. The developed DSS dashboard provides inventory recommendations such as replenishment, promotion monitoring, discount strategies, supplier returns, and product bundling. The results indicate that the proposed system can support more objective and data-driven inventory decisions.

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1. INTRODUCTION

The rapid advancement of digital technology has significantly transformed business operations, particularly in logistics and inventory management. Emerging technologies such as Artificial Intelligence (AI), Machine Learning (ML), Big Data Analytics, and the Internet of Things (IoT) enable organizations to process large-scale data, identify operational patterns, and support faster decision-making. In inventory management, these technologies provide opportunities to improve demand forecasting, optimize stock levels, and enhance warehouse efficiency through data-driven approaches. The integration of intelligent Decision Support Systems (DSS) has become increasingly important as companies require more accurate and adaptive strategies to manage complex inventory conditions (Sihotang, 2023).

However, the implementation of digital systems in many organizations remains limited to transaction recording rather than analytical decision support. This condition was identified at PT Global

Bangunan Jaya, where the company has implemented an Enterprise Resource Planning (ERP) system, namely Microsoft Dynamics AX Retail. Although the ERP system supports daily inventory transactions, its functionality is still primarily descriptive and has not been optimized for predictive analysis or automated recommendations. Consequently, inventory monitoring activities and restocking decisions for numerous Stock Keeping Units (SKU) still rely heavily on manual evaluation, individual experience, and subjective judgment (Agrawal, Chintha, Pamadi, & Aggarwal, 2024).

This limitation contributes to the accumulation of slow-moving products and dead stock, commonly referred to as kill products. These conditions create several operational challenges, including increased storage costs, inefficient utilization of working capital, and reduced warehouse capacity for products with higher turnover rates. Historical inventory conditions at PT Global Bangunan Jaya indicate that products with low movement require a more systematic approach to identify potential risks before they become non-productive inventory (Bergsma, de Ruijt, & Bhulai, 2025).

Previous studies have shown that inventory problems, particularly slow-moving and dead stock issues, require adaptive strategies supported by data analysis. Traditional inventory control methods are often insufficient when dealing with large product variations and dynamic market changes. Therefore, the application of Machine Learning-based Decision Support Systems provides an opportunity to transform historical transaction data into meaningful insights for classification, prediction, and recommendation processes (Amosu, Kumar, Ogunsuji, & Oni, 2024).

In this research, a Machine Learning-based DSS model is proposed to improve inventory management at PT Global Bangunan Jaya. The proposed approach combines Random Forest for inventory status classification, Linear Regression for short-term demand prediction, and K-Means Clustering for product grouping based on movement characteristics and inventory value. Through this integration, the system is expected to provide objective recommendations for inventory handling strategies, including replenishment decisions, discount implementation, product bundling, and supplier return considerations. (Bouazizi, Khedr, Elfaioumy, & Belal, 2024)

The objective of this study is to develop an intelligent inventory management support system capable of detecting potential dead stock risks at an early stage and assisting management in making measurable, data-driven decisions. The proposed system aims to overcome the limitations of conventional inventory monitoring approaches by integrating predictive analytics and automated recommendations into the inventory decision-making process.

2. METHODS

2.1 Research Framework

This research applies a quantitative approach by developing a Machine Learning-based Decision Support System (DSS) for inventory management. The research framework consists of several stages, including data collection, exploratory data analysis, data preprocessing, Machine Learning model development, model evaluation, and DSS implementation (Pahuja, Delir Haghighi, & Jayaraman, 2024).

The proposed framework integrates three Machine Learning approaches, namely classification, regression, and clustering methods. Random Forest is applied to classify inventory status, Linear Regression is used to predict future sales demand, while K-Means Clustering is implemented to identify product groups based on inventory characteristics. The integration of these methods aims to provide a comprehensive analysis of inventory conditions and generate recommendation decisions for product handling (Sitorus, Syahputra, Indra Angkat, & Sartika, 2024).

The implementation of Artificial Intelligence-based DSS allows historical inventory data to be transformed into meaningful information that supports objective decision-making. Previous studies have shown that combining data analytics and Machine Learning techniques can improve inventory planning and supply chain decision processes by utilizing historical patterns and predictive information (Li, Chiu, & Seva, 2022).

2.2 Dataset Collection

The dataset used in this research is inventory management data obtained from PT Global Bangunan Jaya. The dataset consists of 10,000 Stock Keeping Units (SKU) containing product information, category, supplier information, stock condition, historical sales transactions, and supporting inventory attributes.

The collected data represents product movement patterns within inventory activities. These characteristics include sales quantity, transaction frequency, stock value, inventory turnover, and the number of days since the last sale. The dataset is used as the main input for developing Machine Learning models to identify product movement categories and generate inventory recommendations.

The utilization of historical transaction data as input for predictive analysis is commonly applied in inventory optimization because historical patterns provide important information for forecasting demand and identifying inefficient stock conditions (Widyatmoko & Yudoko, 2024).

2.3 Data Preprocessing

Before implementing Machine Learning algorithms, the dataset undergoes preprocessing stages to improve data quality and model performance. The preprocessing process includes data cleaning, handling missing values, data transformation, feature selection, and feature engineering.(Susandri, Defit, & Tajuddin, 2023)

Feature engineering is performed by generating several derived attributes related to inventory behavior, such as total sales within 12 months, transaction frequency, inventory turnover ratio, stock-to-sales ratio, and days since the last sale. These features are used to represent product movement characteristics and support the classification, prediction, and clustering processes (Chernykh, Stepnov, & Lukyanova, 2021).

Data preprocessing is an essential stage in Machine Learning implementation because data quality directly influences model accuracy and reliability. Proper preprocessing allows the model to recognize relevant patterns and reduce noise from the original dataset (Susandri, Zamsuri, Nasution, Efendi, & Alwan, 2025).

2.4 Machine Learning Model Development

1. Random Forest Classification

Random Forest is implemented to classify inventory status into three categories: Fast Moving, Slow Moving, and Dead Stock. This algorithm was selected because it is capable of handling complex relationships between multiple variables and provides good classification performance through ensemble learning techniques (Sá, Carvalho, & Gonçalves, 2025).

The Random Forest model consists of multiple decision trees that combine prediction results to produce a final classification output. In this research, the model uses inventory-related features such as sales activity, stock level, transaction frequency, and product characteristics to determine the movement category of each product (Samson, 2025).

The application of Random Forest for classification problems has been widely used due to its robustness in handling high-dimensional datasets and reducing overfitting compared with individual decision tree models (Susandri et al., 2025)

2. Linear Regression Prediction

Linear Regression is applied to predict product sales demand for the next 12 months. The model analyzes the relationship between historical inventory variables and sales performance to estimate future product demand (Park, Koo, Yang, Han, & Nam, 2024).

The prediction results are used as supporting information in determining inventory strategies, particularly for products requiring replenishment decisions. The predicted demand value provides an estimation of future sales potential and helps management avoid excessive stock accumulation.

Regression-based prediction approaches are commonly utilized in inventory planning because they provide quantitative estimates based on historical data patterns .

3. K-Means Clustering

K-Means Clustering is applied to group products based on similarities in inventory characteristics. The clustering process uses variables related to sales performance, stock condition, and product movement behavior.

The objective of clustering is to identify groups of products with similar patterns, allowing management to understand inventory segmentation more effectively. The resulting clusters are used as additional information for determining appropriate handling strategies.

K-Means is widely used in data mining applications because it can classify large datasets into meaningful groups based on similarity measurements (Rahman et al., 2024).

2.5 Model Evaluation

The performance of each Machine Learning model is evaluated using different evaluation metrics according to its function.

For Random Forest classification, evaluation is performed using accuracy, precision, recall, F1-score, and confusion matrix to measure classification performance.

For Linear Regression, model evaluation uses Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and coefficient of determination (R^2) to measure prediction accuracy.

For K-Means clustering, the optimal number of clusters is determined using the Elbow Method and evaluated using Silhouette Score. These evaluation techniques are used to measure the quality and separation level of generated clusters.

The evaluation process ensures that each model provides reliable analytical results before being integrated into the DSS framework.

2.6 Decision Support System Implementation

The final stage of this research is the implementation of the Decision Support System dashboard. The DSS integrates outputs from Random Forest, Linear Regression, and K-Means models to provide inventory insights and recommendation decisions.

The system provides several features, including product search, inventory status filtering, prediction display, clustering information, priority handling lists, and recommended actions. The generated recommendations include maintaining stock and replenishment, promotion monitoring, discount strategies, supplier return, and product bundling.

The implementation of DSS aims to transform Machine Learning outputs into practical information that can assist management in making faster and more objective inventory decisions (Sihotang, 2023; Tan et al., 2025).

3. FINDINGS AND DISCUSSION

3.1 Exploratory Data Analysis Results

The Exploratory Data Analysis (EDA) process was conducted to understand the characteristics, distribution, and relationships between inventory variables before implementing Machine Learning models. The analysis provides initial information regarding product movement patterns, sales behavior, and inventory conditions that influence the decision-making process.

The dataset analysis shows that inventory conditions consist of three main product movement categories, namely Fast Moving, Slow Moving, and Dead Stock. These categories represent differences in product demand levels and inventory turnover characteristics. Fast Moving products indicate products with high sales activity, while Slow Moving and Dead Stock products require further analysis because they have a higher risk of inventory accumulation.

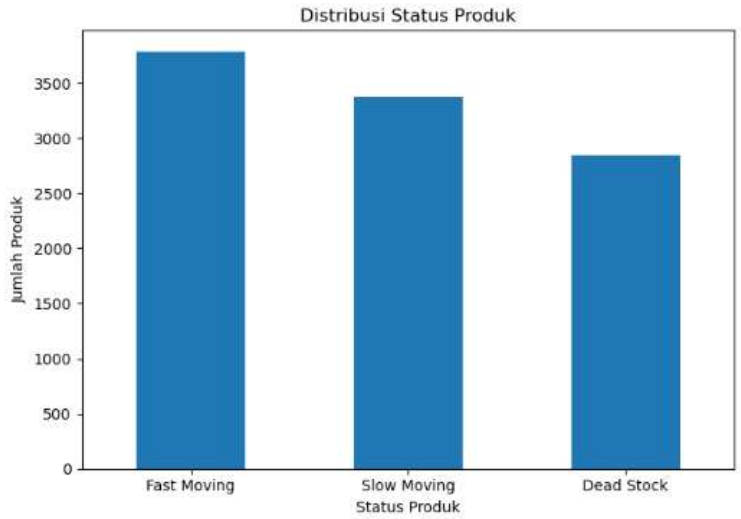

Figure 1. Distribution of Inventory Status

The correlation analysis was also performed to identify relationships between numerical variables used in the Machine Learning process. The correlation matrix shows that several variables have relationships related to inventory movement, such as total sales, transaction frequency, stock level, and days since the last sale. Variables related to sales activity show an important relationship in determining product movement patterns.

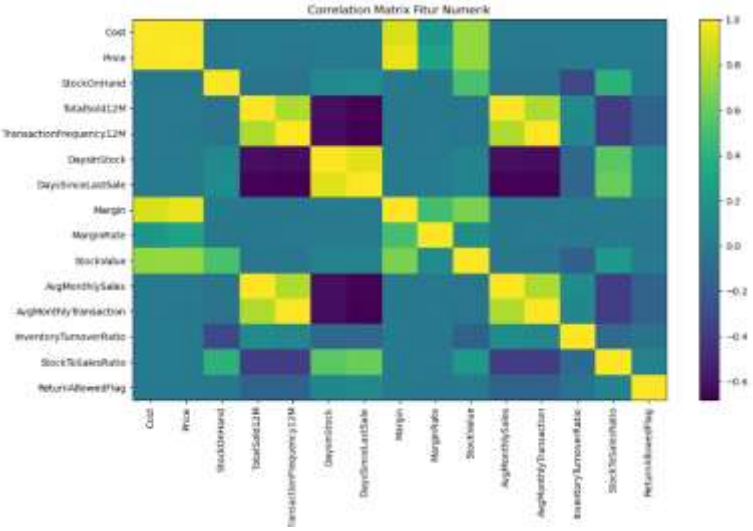

Figure 2. Correlation Matrix of Inventory Variables

The EDA results provide an initial understanding of the dataset characteristics and become the basis for selecting relevant features in the preprocessing and modeling stages. This process helps ensure that the developed models use representative variables for inventory analysis.

3.2 Random Forest Classification Results

The Random Forest algorithm was implemented to classify inventory products into three categories: Fast Moving, Slow Moving, and Dead Stock. The classification model utilizes inventory-related features, including sales activity, stock information, transaction frequency, and product characteristics.

The evaluation results show that the Random Forest model achieved an accuracy value of 88.4%, with precision, recall, and F1-score values of 0.88. These results indicate that the model has good capability

in recognizing inventory movement patterns and distinguishing product categories based on historical data.

Classification Report:

	precision	recall	f1-score	support
Dead Stock	0.90	0.89	0.89	569
Fast Moving	0.89	0.94	0.91	757
Slow Moving	0.86	0.82	0.84	674
accuracy			0.88	2000
macro avg	0.88	0.88	0.88	2000
weighted avg	0.88	0.88	0.88	2000

Figure 3. Performance Evaluation of Random Forest Model

The Random Forest algorithm was implemented to classify inventory products into three categories: Fast Moving, Slow Moving, and Dead Stock. The classification model utilizes inventory-related features, including sales activity, stock information, transaction frequency, and product characteristics.

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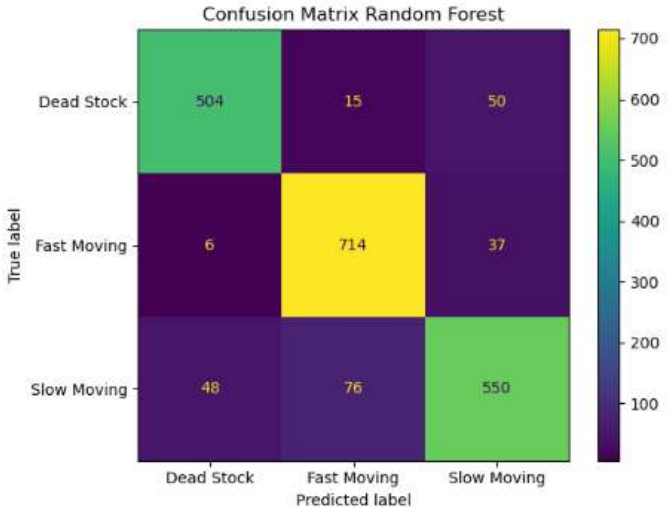

Figure 4. Confusion Matrix of Random Forest Classification

The results indicate that Random Forest can effectively identify products with potential inventory problems, especially products categorized as Dead Stock. The classification output becomes an important component in the DSS because it provides early information regarding product conditions that require further action.



Figure 5. Feature Importance of Random Forest Model

The feature importance analysis shows that variables related to product movement and sales performance contribute significantly to classification decisions. This finding indicates that historical sales behavior and inventory activity are important factors in determining product status.

3.3 Linear Regression Prediction Results

The Linear Regression model was developed to estimate future product sales demand based on historical inventory data. The prediction output is used to support inventory planning decisions, particularly in determining stock replenishment strategies.

The model evaluation was conducted using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and coefficient of determination (R^2). The obtained results show:

```
print("Mean Absolute Error (MAE):", round(mae,2))
print("Root Mean Squared Error (RMSE):", round(rmse,2))
print("R2 Score:", round(r2,3))
```

```
Mean Absolute Error (MAE): 100.44
Root Mean Squared Error (RMSE): 140.27
R2 Score: 0.681
```

Figure 6. Performance Evaluation of Linear Regression Model

The R^2 value of 0.681 indicates that the model is capable of explaining approximately 68.1% of the variation in sales demand patterns based on the selected inventory variables. Meanwhile, the MAE and RMSE values indicate the average prediction error generated by the model.

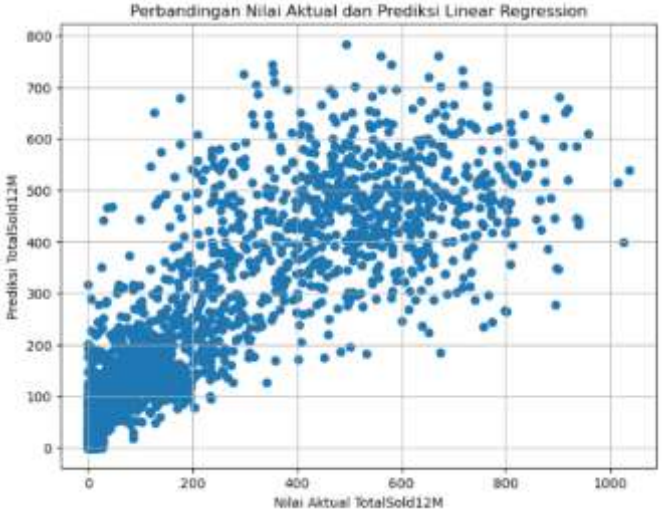

Figure 7. Comparison Between Actual and Predicted Sales Using Linear Regression

The visualization shows that the predicted values generally follow the direction of the actual sales distribution, although several differences occur due to variations in product demand patterns. The prediction results provide additional information for management in determining stock availability and reducing the possibility of excessive inventory.

3.4 K-Means Clustering Results

The K-Means algorithm was applied to group products based on similarities in inventory characteristics. The clustering process uses variables related to sales performance, stock condition, and product movement behavior.

The optimal number of clusters was determined using the Elbow Method. The evaluation result indicates that three clusters provide the most appropriate grouping structure for the inventory dataset.

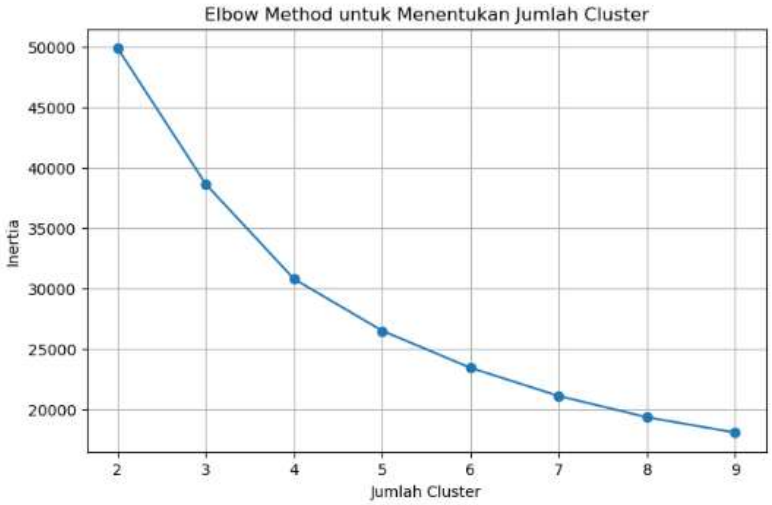

Figure 8. Elbow Method for Determining Optimal Cluster

Illustrates the process of determining the optimal number of clusters in the K-Means algorithm based on the inertia value. The graph shows that the reduction in inertia decreases significantly at the beginning and starts to become more stable after reaching a certain number of clusters. Based on the elbow point observed in the graph, three clusters were selected as the optimal number of clusters for the inventory dataset.

The selected three clusters represent different inventory movement characteristics, namely Fast Moving Pattern, Slow Moving Pattern, and Dead Stock Pattern. These clustering results provide additional information for the Decision Support System (DSS) to identify product characteristics and determine appropriate inventory handling strategies.

```
print(
    "Silhouette Score:",
    round(score,3)
)
```

```
Silhouette Score: 0.336
```

Figure 9. K-Means Silhouette Score Results

The clustering evaluation using Silhouette Score resulted in a value of **0.336**, indicating that the generated clusters have sufficient separation based on product characteristics.

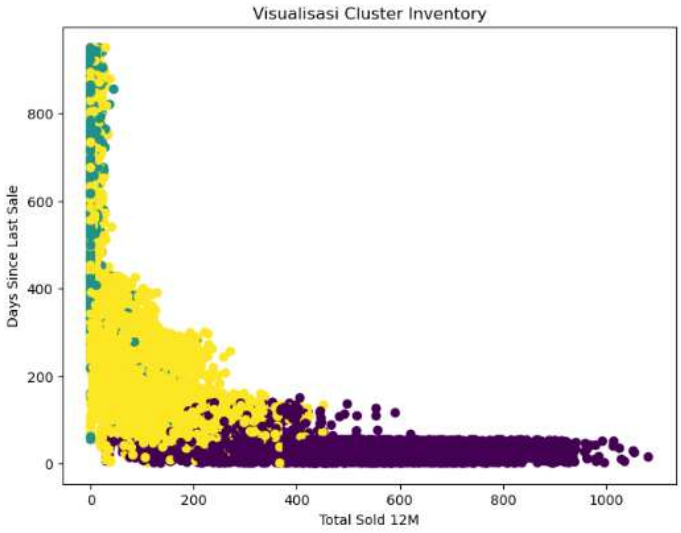

Figure 10. Inventory Cluster Visualization Using K-Means

The visualization illustrates three distinct inventory movement patterns: Fast Moving Pattern, which represents products with high sales activity and relatively short intervals between transactions; Slow Moving Pattern, which indicates products with moderate sales activity that require regular monitoring to prevent excessive inventory accumulation; and Dead Stock Pattern, which describes products with low sales activity and extended periods without transactions. These patterns help identify inventory movement levels and support more effective inventory management and stock control decisions.

The clustering results provide additional insight into inventory segmentation and support the DSS recommendation process by identifying product groups that require different handling strategies.

3.5 Decision Support System Implementation Results

The outputs from Random Forest, Linear Regression, and K-Means were integrated into a Decision Support System dashboard to provide practical inventory recommendations. The dashboard presents product information, inventory status, sales prediction, cluster category, priority handling, and recommended actions.



Figure 11. DSS Inventory Management Dashboard

The system provides several analytical features, including product search, inventory status filtering, top priority product identification, recommendation summaries, and data export functionality.



Figure 12. Product Recommendation Search Interface

Figure 9. Product Recommendation Search Interface illustrates the product search and recommendation feature implemented in the Decision Support System (DSS) dashboard. This feature allows users to search for specific products and obtain detailed inventory analysis results based on the integrated Machine Learning models.

In this example, the system displays information for Cat Kayu Premium D, including product category, inventory status, 12-month sales prediction, cluster classification, and recommended inventory action. The product is classified as Fast Moving with a prediction of 502 units for the next 12 months and belongs to the Fast Moving Pattern cluster. Based on these results, the DSS provides a recommendation to maintain stock levels and perform replenishment to ensure product availability.

This feature enables users to quickly access data-driven insights and supports more objective inventory decisions by combining classification, prediction, and clustering results into a single recommendation interface.

Based on the integrated model results, the DSS generates several inventory handling recommendations, including:

- maintaining stock and performing replenishment for Fast Moving products,
- conducting promotion and stock monitoring for Slow Moving products,
- applying discount strategies, product bundling, or supplier returns for Dead Stock products.



Top Prioritas Penanganan Produk

	ProductName	Category	StockValue	DaysSinceLastSale	Recommendation
1,644	Primer Cat Premium E	Cat	257,889	950	Diskon Harga
830	Waterproofing Ekonomis 50kg	Perekat & Kimia	4,057,936	949	Diskon Harga
293	MCB Standard 1/2 inch	Peralatan Listrik	63,639,320	947	Return Supplier
73	Pipa PVC Heavy Duty 3/4 inch	Pipa	8,074,176	947	Diskon Harga
1,888	Semen Portland Premium 60x60	Semen	17,472,598	945	Bundling dengan Se
1,572	Besi Hollow Premium 1/2 inch	Besi	16,275,215	944	Bundling dengan Be
1,769	Pipa Besi Premium A	Pipa	21,368	942	Bundling dengan Pi
641	Kuas Retail 60x60	Alat Bangunan	159,588,819	940	Return Supplier
1,999	Semen Portland Retail D	Semen	13,037,895	938	Bundling dengan Se
1,505	Mozaik Premium B	Keramik	47,669,928	936	Bundling dengan Mc

Figure 13. Top Priority Inventory Handling Recommendation

This figure presents a ranked list of products that require prioritized management based on inventory analysis and the DSS recommendations. Each row displays the product name, category, stock value, days since the last sale, and the recommended action. High-priority products include items with long storage durations or large stock values, such as *Primer Cat Premium E* (Cat) and *Waterproofing Ekonomis 50kg* (Perekat & Kimia), which are recommended for discounting, while items like *MCB Standard 1/2 inch* (Peralatan Listrik) are suggested to be returned to the supplier. Other products are recommended for bundling with fast-moving items to optimize inventory turnover. This figure illustrates how the DSS identifies critical inventory items and provides targeted actions to reduce slow-moving and dead stock effectively.

The implementation results demonstrate that the DSS is capable of transforming Machine Learning outputs into actionable information. The system helps management identify inventory risks earlier and supports more objective decision-making compared with conventional manual evaluation.

4. CONCLUSION

This research successfully developed a Machine Learning-based Decision Support System (DSS) for inventory management by integrating classification, prediction, and clustering approaches. The proposed system utilizes historical inventory and sales data to provide analytical insights and support data-driven decision-making in managing product movement and stock conditions.

The implementation of the Random Forest algorithm successfully classified inventory conditions into three categories: Fast Moving, Slow Moving, and Dead Stock. The model achieved an accuracy of 88.4%, with precision, recall, and F1-score values of 0.88, indicating that the model was able to identify product movement patterns effectively. Furthermore, the Linear Regression model provided sales demand predictions with an R^2 value of 0.681, demonstrating its capability to estimate future sales trends based on historical inventory data.

The K-Means clustering method successfully grouped products into three inventory patterns, namely Fast Moving Pattern, Slow Moving Pattern, and Dead Stock Pattern, with a Silhouette Score of 0.336. These clustering results provided additional information regarding product characteristics and supported the determination of appropriate inventory handling strategies.

The integration of these Machine Learning models into the DSS dashboard enabled the transformation of analytical results into practical recommendations, including stock replenishment, promotion monitoring, discount strategies, supplier returns, and product bundling. The developed system provides a more objective and structured approach compared with conventional inventory evaluation methods, allowing management to identify inventory risks and prioritize product handling decisions more effectively.

For future development, the system can be improved by integrating real-time ERP data access, utilizing longer historical datasets, and applying more advanced forecasting methods to improve prediction accuracy and adaptability to changing market conditions.

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