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Development of a Machine Learning-Based Predictive Model for Forecasting Spare Part Requirements at the Warehouse of PT. Setia Karya Transport (Great Giant Foods) Way Lunik

Muhammad Afdhaluddin[1], Lailatur Rahmi[*2], Elsa Dwi Agresty[3]
[1,3]Department of Computer Science, Lampung University, Bandar Lampung
[2] Department of Management Informatics, Politeknik Negeri Sriwijaya, Palembang

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ABSTRACT

Efficient spare part management plays a crucial role in supporting operational continuity at PT. Setia Karya Transport (Great Giant Foods). The current spare part forecasting process is still reactive and relies on periodic evaluations, resulting in potential inefficiencies in procurement planning. This study aims to develop a machine learning-based predictive model to forecast spare part requirements using historical transaction data from January to July 2025. The research applied three modeling scenarios: (1) a hybrid model combining Support Vector Regression (SVR), Random Forest, and Statistical methods; (2) pure statistical methods with zero-ratio classification; and (3) the XGBoost algorithm with zero-ratio classification. Model performance was evaluated using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) metrics. The results showed that the hybrid approach achieved the best performance with an MAE of 2.919 and an RMSE of 8.056, indicating higher prediction accuracy compared to other models. The findings demonstrate that integrating machine learning with statistical approaches can effectively enhance forecasting accuracy and support data-driven decision-making in warehouse management.

Keywords : Machine Learning, Forecasting, Spare Part, Random Forest, Support Vector Regression

Corresponding Author:

Muhammad Afdhaluddin
Department of Computer Science
Lampung University
Lampung, Indonesia
Email: mafdhal.uddin@fmipa.unila.ac.id

1. Introduction

Great Giant Foods (GGF) is one of the largest integrated agribusiness companies in Indonesia that produces and distributes horticultural, livestock, and processed food products on a national and international scale. To support its smooth operations, GGF has a number of supporting units, one of which is PT. Setia Karya Transport, which plays a special role in managing land transportation, divides into export-import, generator sets, internal group operations, harvesting, supply tanks, and farm equipment units that support harvesting operations at Great Giant Pineapple.

PT. SKT's Warehouse division manages a structured process for receiving and issuing goods to maintain spare part availability for operational vehicles. The warehouse recording system incorporates material classification by rotation speed: slow moving, medium moving, and fast moving. This classification enables the team to analyze stock rotation patterns and effectively plan for inventory requirements. Inventory management is the process of monitoring and controlling stock levels to ensure operational continuity, reduce costs, and balance the risks of excess or shortage of inventory[1]. In the context of warehousing, this management includes the processes of procurement, storage, and distribution of goods so that spare parts requirements can be met in a timely and efficient manner[2]. By applying these principles, the warehouse division can align stocking strategies with actual usage patterns, enabling better decision-making regarding restocking frequency, safety stock determination, and prioritization of high-demand components.

Despite the absence of major issues such as overstocking or understocking, the current spare part demand management process remains reactive and depends on technician expertise and periodic evaluations. To improve its effectiveness, one new approach that can be applied is a predictive system. A predictive system is a system that utilizes historical data to identify patterns, find relationships between data, and generate predictions about future needs[3]. In the prediction process, a forecasting approach is used, which is a method of estimating future events based on past and current data, with the aim of reducing demand estimation errors[4]. A predictive approach enables companies to shift from traditional, experience-based planning to a more objective and measurable method, resucing the risk of human error and ensuring that spare part availability is always aligned with real operational requirements.

The implementing machine learning-based predictive models presents a strategic opportunity to enhance logistics efficiency and procurement planning in warehouse management. Leveraging historical spare part usage data, these models can estimate future requirements with greater accuracy and adaptability. Predictive models are not only capable of recognizing trends and seasonal demand fluctuations, but they can also detect anomalies or sudden spikes in usage that may require preventive actions from the warehouse team.This aligns with findings that machine learning and deep learning methods significantly improve demand forecasting accuracy in logistics environments[5]. Moreover, research on spare part demand forecasting shows that transfer-learning based ML models can handle intermittent demand and improve stability and precision of predictions compared to traditional methods[6]. This approach not only prevents the risk of stock shortages that may not be detected manually, but also enables more optimal, efficient, and data-driven procurement arrangements. Therefore, this study aims to design a predictive model for spare part requirements using a machine learning approach to strengthen decision-making in the warehouse division of PT. Setia Karya Transport.

One new approach that can be taken is the application of a Machine Learning-based predictive model (ML) that can learn patterns from historical data and generate more accurate predictions by considering data variability and complexity.Machine learning is a branch of artificial intelligence that enables computers to learn from data and improve their performance without explicit programming instructions[7]. Some commonly used prediction methods in spare part forecasting include Support Vector Regression (SVR), which is a modification of Support Vector Machine that solves regression problems by finding the best hyperplane and minimizing error[8]. Exponential Smoothing, a technique that gives greater weight to the latest data in forecasting[9]. Moving Average, a forecasting method that calculates the average demand for several previous periods and moves over time[10]. Croston's Method, a development of exponential smoothing used to predict intermittent or irregular demand[11]. These methods were selected because they can accommodate different patterns of demand behavior, and each technique offers advantages depensing on data characteristics such as seasonality, fluctuation, and irregular consumption frequency.

In a study by Ifraz et.al. [12], ML models such as Support Vector Regression (SVR) were shown to produce better forecasts than conventional methods in managing spare parts for bus fleets. However, simple statistical methods remain relevant in certain contexts. In a study conducted by Yuniarti [13] on the analysis of the Single Exponential Smoothing method in sales forecasting, the prediction results achieved an accuracy of 63,7%. Meanwhile, Noviadry Nur Tamtama and rahmawati Riantisari [14] analyzed demand forecasting using the Moving Average method in a case study on Exist Auto Detailing and found that the method produced sufficiently accurate predictions. Futhermore, the application of the Croston method, as presented in the research by Simamora et al. [15] on forecasting the demand for LCV Bushing Struthbar spare parts, demonstrated that this method could generate forecasts with a relatively small error value of 0.6, indicating its effectiveness in handling intermittent demand. The comparison of these studies shows that selecting the appropriate forecasting method greatly depends on the data pattern and the operational objectives of the warehouse.

However, in the implementation of this internship project, the development of predictive models was limited to simulation and was not directly integrated into the company's prediction or operational systems. This was due to the company's internal policy, which did not allow the development or modification of system without strict licensing procedures.Therefore this activity focused on data analysis, predictive model development, and model performance evaluation based on available historical data. Although the model implementation is still in the testing phase, the results obtained provide valuable insights for future warehouse planning improvements.

Through this approach, it is hoped that the simulation results can provide an overview of the potential application of machine learning in managing spare part requirements in the future, as well as provide input for the company in making data-driven decisions. This initiative also opens opportunities for future developments, such as integrating the predictive model into the warehouse managements system (WMS) or building a dashboard that visualizes prediction outcomes, enabling management to monitor and respond to inventory needs in real time.

2. Research Method

This study was conducted at the Warehouse Division of PT. Setia Karya Transport (Great Giant Foods), Way Lunik, Bandar Lampung, over a period of 40 days, from June 16, 2025 to July 26, 2025. The research focused on developing a machine learning-based predictive model to forecast spare part requirements based on historical transaction data.

2.1 Data Sources

The Data in this study were obtained from the internal documentation of PT. Setia Karya Transport, particularly from the warehouse transaction records. Two types of data were utilized:

1. Primary Data
   Primary data is data collected independently by individual or groups directly from the research object for the purposes of related studies, which can be in the form of interviews or observations[16]. Collected through direct observation and interviews with warehouse and maintenance staff. This data includes spare part expenditure records based on SPBI (Internal Goods Request Letter) documents showing the vehicle unit code, material code, material name, request quantity, request date, and the name of the requesting mechanic, in the data also includes transaction procedures, and operational flow of spare part distribution.
2. Secondary Data
   Secondary data is data obtained through intermediaries such as books, records, journals, or reports found in archives or documentation[17]. This data includes historical spare part usage data from January to July 2025, recorded in Excel format. Each record contains information such as request date, material code, material description, quantity, unit, goods issue status, and requesting mechanic, which form the basis for the needs analysis process and predictive model development.

2.2 Data Collection Methods

Several data collection techniques were applied:

1. Observation
   Direct observation of spare part request, storage, and issuance processes in the warehouse division. Observations were made by following the workflow of warehouse staff, including when receiving request documents (SPBI), checking the availability of goods, and recording distribution expenses. Observation is one of the key qualitative data collection techniques, allowing researchers to directly capture behaviours and operational processes as they occur[18].
2. Interview
   Structured and unstructured discussions with the warehouse head and staff to understand decision-making processes and stock management strategies. Interviews are an essential qualitative technique that help researchers explore experiences, reasoning, and decision-making from participants directly [19]. Through interviews, researchers can obtain deeper contextual understanding that may not be visible from observational or written data alone[20].
3. Documentation Study
   Collection and examination of internal documents such as SPBI forms, stock movement reports, and Excel transaction data to identify historical usage patterns. Document analysis in one of the valid methods to verify and cross-check findings from observation and interviews, making it crucial in

qualitative research[21]. Reviewing documents also supports data triangulation and allows researchers to analyse historical patterns objectively[22].

2.3 Model Development Method

The predictive model development followed a structured approach consisting of the following stages:

1. Observation of Business Process : Understanding the warehouse workflow, from spare part request to procurement.
2. Data Understanding and Preprocessing: Cleaning missing or duplicate entries,standardizing date formats, aggregating daily data into weekly intervals, and normalizing variable scales.
3. Data Splitting : Dividing data into training and testing sets with an 80:20 ratio.
4. Model Training : Applying three experimental scenarios :
   - Experiment 1 : Machine learning algoritms Support Vector Regression (SVR) and Random Forest, combined with statistical models such as Exponential Smoothing, Croston's Method, and Moving Average.
   - Experiment 2 : Pure statistical methods with zero-ratio classification.
   - Experiment 3 : XGBoost algorithm combined with zero-ratio classification.
5. Model Evaluation
   The model's performance was evaluated using two common regression metrics, Mean Absolute Error (MAE) and Root Mean Squarred Error (RMSE). These metrics were used to measure the accuracy and deviation of predicted values form the actual data. The MAE repsents the average magnitude of the prediction errors, without considering their direction, which is calculated by measuring the average absolute difference between the actual value and the predicted value[23]. Meanwhile, the RMSE indicates the magnitude of the prediction error by giving higher weight to large errors due to the squaring process, where the smaller the RMSE value, the more accurate the model[24].
   The mathematical formulations are shown in equations (1) and (2).

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|A_t - F_t| \tag{1}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n}} \tag{2}$$

Where :

- A_t = actual value
- F_t = forecasted (predicted) value
- n = total number of observations

A smaller value of MAE or RMSE indicates a better predictive model.

2.4 Research Flow

The process begins with systematic data collection and preprocessing, ensuring that the dataset is clean, complete, and suitable for time-series forecasting. This stage includes handling missing values, detecting anomalies, performing normalization if required, and structuring historical demand data into an analyzable format. After preprocessing, several forecasting models are selected and developed based on their suitability for spare part demand prediction. Each model is then trained using historical data and evaluated through a series of performance metrics to determine its predictive accuracy. In this study, the primary evaluation indicators used are Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), as both metrics effectively measure the magnitude of forecasting errors. The model that achieves the lowest MAE and RMSE values is identified as the most optimal and thus selected for generating the final demand forecasts. The overall methodological workflow for model development, from initial data processing to model evaluation and selection, is clearly illustrated in Figure 1.

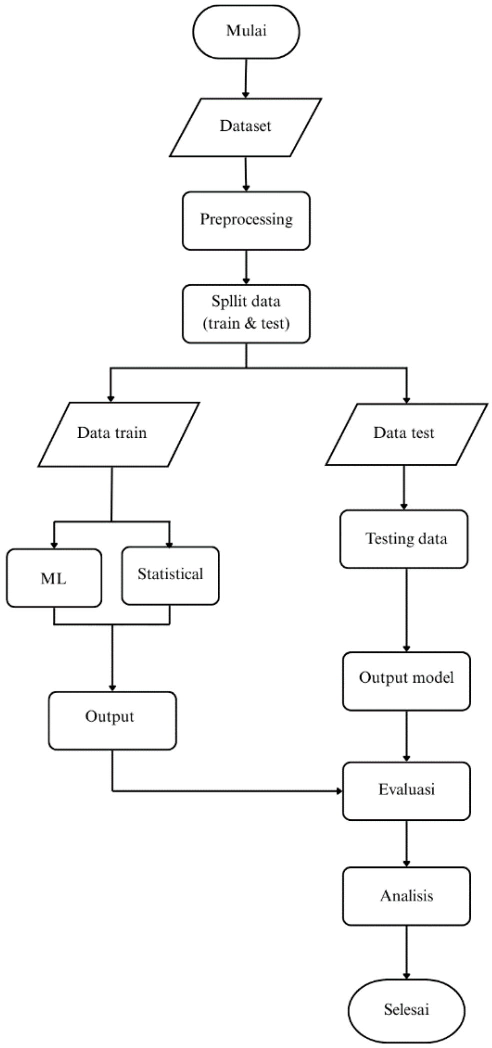

Figure 1. Flowchart of predictive model development process

3. Result and Discussion

3.1. Data Processing and Model Training

The historical data used comes from spare part expendicture records at the PT. Setia Karya Transport warehouse for the period January-July 2025. The data consist of the request date, material code, material description, amount used, vehicle unit, Goods issue status, and document number

The processing stages are carried out in several steps, starting with data cleaning to remove duplicates, handle missing values, and standardize date formats. Next, aggregation is carried out, which is converting daily data into weekly data so that demand patterns are easiesr to analyze and see clearly. After that, normalization is performed and the dataset is devided into two parts, namely 80% as training data and 20% as testing data to ensure that the model can be evaluated properly.

The tested model consists of three main approaches, each designed to address different characteristics of spare part demand data. First, a hybrid approach is employed by combining Support Vector Regression (SVR), Random Forest, and several statistical techniques. This combination leverages the strengths of machine learning in capturing nonlinear relationships while maintaining the stability and interpretability of statistical components. Second, a fully statistical-based approach is implemented using methods such as Exponential Smoothing, Moving Average, and Croston, which are particularly effective for modeling intermittent and highly irregular demand patterns commonly found in spare part consumption. These methods help capture trends, seasonality, and sporadic demand occurrences with greater precision. Third, a machine learning approach is developed using the XGBoost algorithm, which is further enhanced with a zero-ratio balancing technique to address the imbalance between zero-demand periods and active demand periods. This adjustment ensures more reliable forecasting performance and reduces bias in datasets dominated by infrequent demand events.

3.2. Model Evaluation

The testing was conducted in three different experiments using two regression evaluation metrics, namely Mean Absolute Error (MAE) and Root Mean Squarred Error (RMSE). For the first experiment with the application of SVR and Random Forest assisted by statistical methods, the test results showed an MAE accuracy value with an average of 2.919 and an RMSE average of 8.056. The second experiment with the application of statistical methods with zero ratio classification showed MAE results with an average of 4.069 and RMSE with an average of 11.213. Meanwhile, in the third experiment with the application of the XGBoost algorithm and zero ratio classification method, the results obtained were MAE with an average of 13.768 and RMSE with an average of 16.700. The following table compares the evaluation results.

Table 3 1 Comparison table of mode evaluation results

Model	Metric Evaluasi (Rata-rata)	
	MAE	RMSE
SVR, Random Forest and statistical method	2.919	8.056
Statistical method and zero ratio	4.069	11.213
XGBoost and zero ratio	13.768	16.700

To provide a clearer picture of how these evaluation metrics are calculated, here is a simple example of calculation using three actual data points nd prediction results.

Table 3 2 Table of actual data and prediction sample

Data Aktual	Prediksi
85	78
60	67
60	60,7

The calculation for each metric is as follows :

1. Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|A_t - F_t| \tag{3}$$

$$MAE = \frac{1}{3}\big((85-78) + (60-67) + (60-60{,}7)\big)$$

$$= \frac{1}{3}(7 + 7 + 0{,}7) = \frac{14{,}7}{3} = 4{,}9$$

2. Root Mean Squarred Error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n}} \tag{4}$$

$$RMSE = \sqrt{\frac{((85-78)^2 + (60-67)^2 + (60-60{,}7)^2)}{3}}$$

$$RMSE = \sqrt{\frac{((7)^2 + (7)^2 + (0{,}7)^2)}{3}}$$

$$RMSE = \sqrt{\frac{(49 + 49 + 0{,}49)}{3}} = \sqrt{\frac{98{,}49}{3}}$$

$$RMSE = \sqrt{32{,}83} = 5{,}73$$

Based on the results of the above example calculation, the MAE value is 4.9 and the RMSE value is 5.73. The MAE value indicates that, on average, the prediction results have a deviation of 4.9 units from the actual value. Meanwhile, the slightly higher RMSE value of 5.73 indicates that there are several larger errors because RMSE gives greater weight to large differences through the squaring process.

Here is a graph comparing historical data and prediction results.

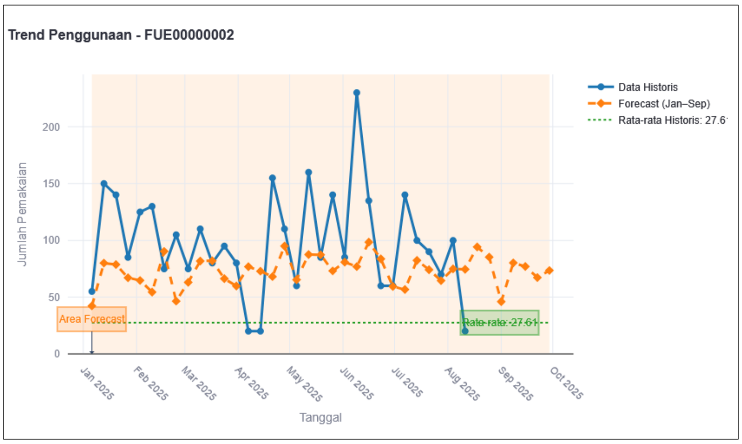

Figure 1. Comparison graph of actual data and predictions (Experiment 1)

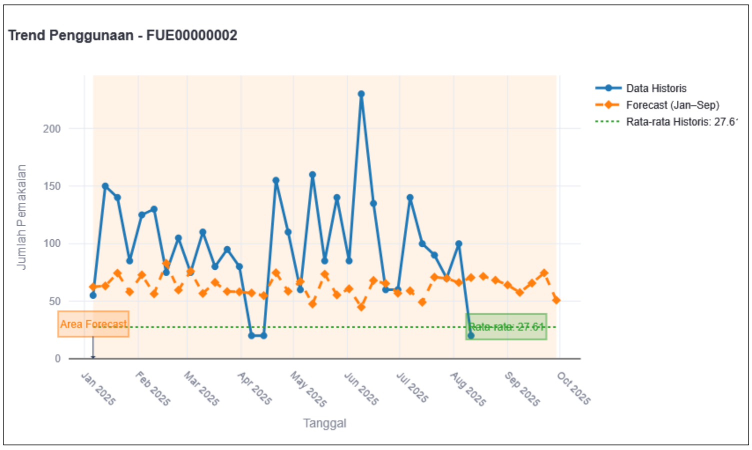

Figure 2. Comparison graph of actual data and predictions (Experiment 2)

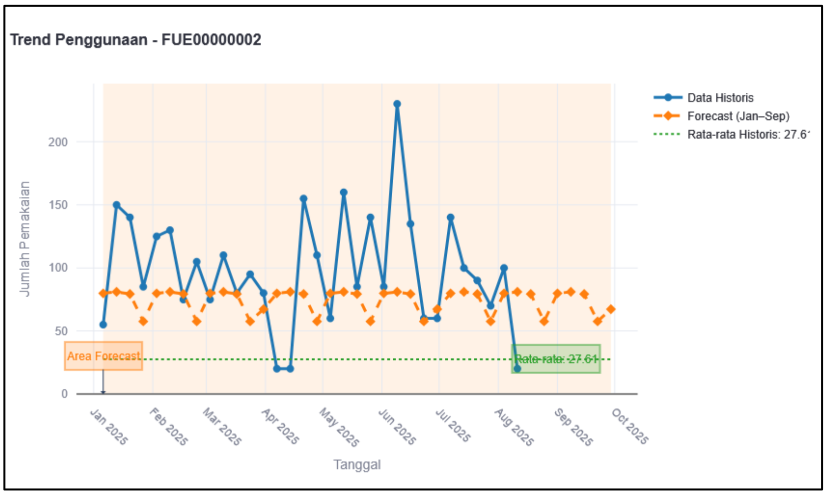

Figure 3. Comparison graph of actual data and predictions (Experiment 3)

3.3. System Implementation

Implementation is the stage of generalizing the constructed model into a program[25]. In this study, the model prediction results are presented in the form of web-based visualizations. This visualization is built using the streamlit framework with the Python programming language, which is displayed through a localhost server. The visualization was created using Visual Studio code as the code editor. In this study, the web was not used to train or build models, but rather to visualize the results of spare part demand forecasts. Through this website, users can view historical trends and predictions in the form of graphs and tables, as well as obtain a summary of forecast information per material.

3.3.1 Page Dashboard by Material

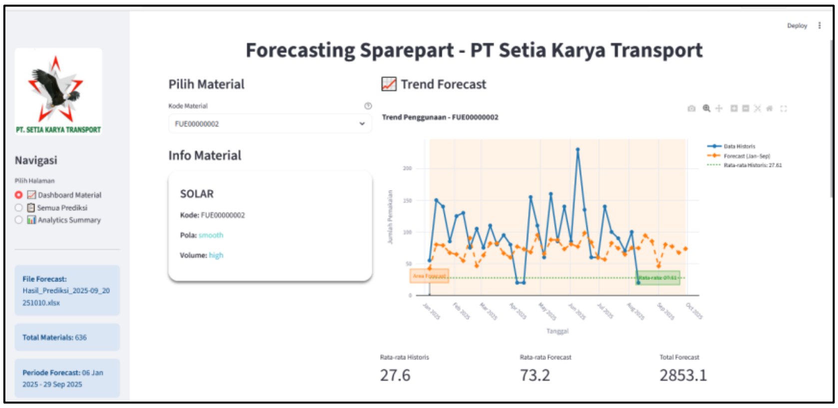

Figure 4. Dashboard by material (graph)

The page shown in Figure 4 presents a comparison graph between historical data and prediction results for a specific material, serving as an analytical interface for evaluating forecasting performance. Users can easily select the material they wish to analyze through the dropdown menu, allowing flexible navigation across different spare part categories. Once a material is selected, the system automatically displays its historical usage data alongside the predicted demand generated by the chosen forecasting model. The graph illustrates usage patterns over time, enabling users to observe fluctuations, seasonal trends, and irregular demand behaviors.

In addition to the visual comparison, the page also provides detailed material information, including the material name, demand pattern classification, and volume class. These attributes help users understand the characteristics of each material and assess whether the selected forecasting model aligns with its specific demand behavior. By presenting both historical values and predicted points in a clear and integrated format, the display offers a comprehensive visual overview of predictive accuracy. This assists users in identifying deviations, evaluating model reliability, and determining whether forecast adjustments are necessary. Ultimately, this page supports more informed decision-making in inventory planning and spare part management.

3.3.2 Weekly Forecast Detail

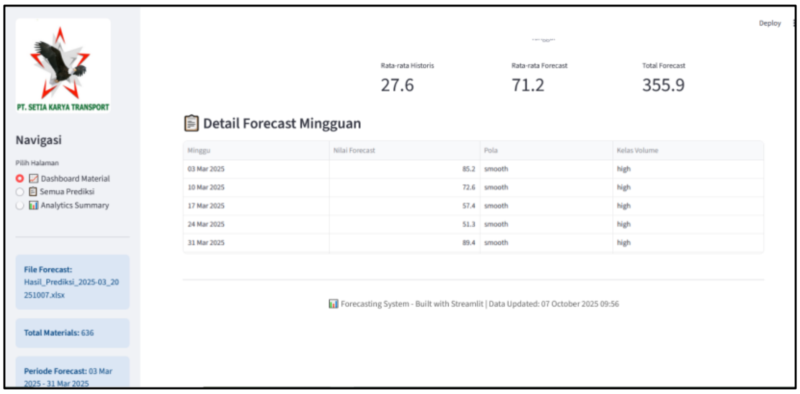

Figure 5. Weekly forecast detail

This weekly forecast detail table is located on the same page as the per-material comparison graph, providing users with a more granular view of predicted demand. The table displays several key pieces of information, including the week period, the forecasted value for each interval, the type of forecasting model applied, the identified demand pattern, and the corresponding volume class. By presenting these elements together, the system enables users to understand not only the numerical forecasts but also the underlying characteristics that influence prediction reliability. Additionally, the system automatically aggregates weekly forecasts into a total monthly forecast value, offering a concise summary that supports higher-level planning. This monthly aggregation greatly simplifies the process of estimating material requirements, ensuring that planners can align procurement schedules, budget allocations, and inventory strategies with anticipated consumption more effectively. Overall, the table enhances transparency and usability within the forecasting workflow.

3.3.3 Page All Spare Part Forecats

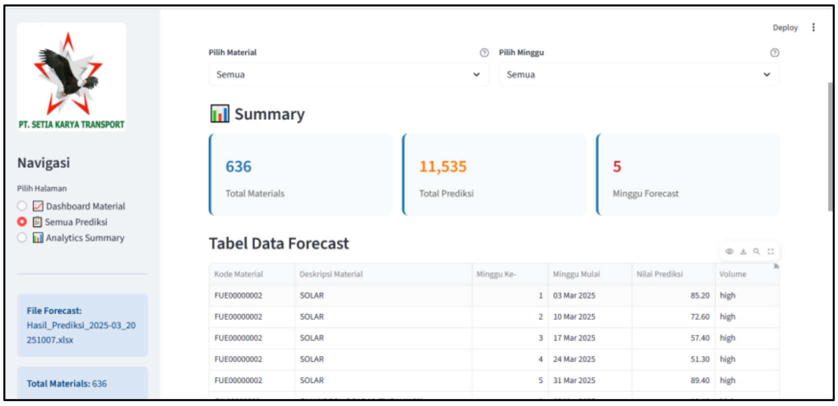

Figure 6. All spare part forecasts page

This page displays a list of predicted material requirements in table form. The information displayed includes the material code, material description, start date of the prediction period, prediction results, and the type of model used. This feature makes it easy to monitor the prediction results comprehensively without having to open each material individually. In addition, there is a feature to download data in CSV or Excel format so that the prediction results can be easily used for further analysis or documentation.

3.3.4 Analytics Dashboard

Figure 7. Analytics Dashboard (demand model and pattern distribution)

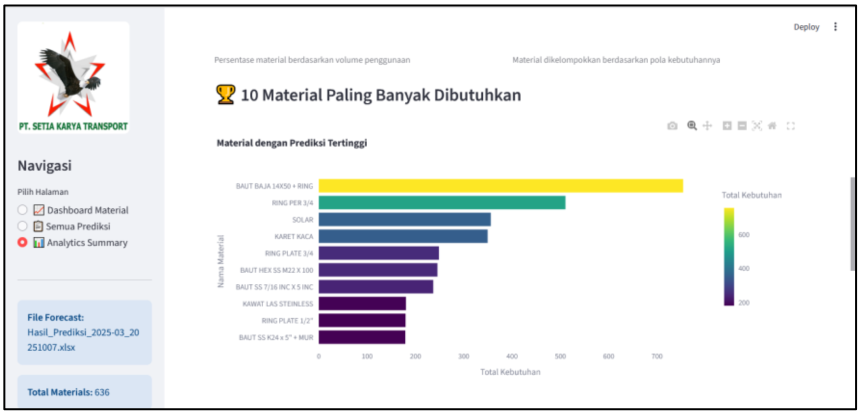

Figure 8. Analytics Dashboard (top 10 highest forecast materials)

This dashboard provides an analytical summary of the prediction results, displaying information related to model distribution, demand pattern distribution, and the top 10 materials with the highest predictions.

4. Conclusion

Based on the evaluation of three modeling approaches, it was concluded that the hybrid combination of Support Vector Machine (SVM) and Random Forest with statistical methods (Experiment 1) was the most optimal solution for forecasting spare part requirements at PT Setia Karya Transport. This is demonstrated by the lowest error values, namely Mean Absolute Error (MAE) of 2.919 and Root Mean Squared Error (RMSE) of 8.056.

This finding confirms that the essence of machine learning lies in the selection of the right methodology, not merely the complexity of the algorithm. The proposed hybrid approach successfully combines the flexibility of machine learning in recognizing complex patterns with the stability of statistical methods in time series data processing, resulting in a robust model for intermittent data. The results of this study prove that the integration of multidisciplinary methodologies can provide a more effective forecasting solution than a single approach.

However, the results obtained need to be reevaluated because there are several factors that can affect model performance, such as limited historical data, imbalance in demand distribution between spare part types, and potential seasonal variability that is not fully represented in the dataset. Therefore, further research with more complete and representative data is expected to improve model reliability and produce more accurate and stable predictions.

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