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IMPLEMENTATION OF THE MOVING AVERAGE ALGORITHM IN A WEB-BASED FOOD AND BEVERAGE RAW MATERIAL STOCK REQUIREMENT PREDICTION INFORMATION SYSTEM

Ainia Hasna Salsabila[1], Bambang Agus Herlambang[2], Ramadhan Renaldy[3]
[123]Informatika, Fakultas Teknik dan Informatika, Universitas PGRI Semarang, Semarang
E-mail: Ainiahasna03@gmail.com[1], author_2@mail.com[2]

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Abstract

Inventory is a critical component in business operations, particularly in the Food and Beverages (F&B) sector, which demands accurate management to mitigate the risks of stockouts and overstocking. However, many MSMEs still rely on conventional methods based on subjective assumptions, which are prone to errors and unable to accommodate demand fluctuations. This research aims to develop a web-based raw material stock forecasting information system integrated with the Single Moving Average (SMA) method to enhance inventory management efficiency. The system development follows a prototyping approach, encompassing data collection, quick design using UML, prototype construction using PHP Laravel and Python, evaluation, and system refinement. The dataset utilized consists of 12 periods of monthly financial reports from Benjiro Sushi, Lamper branch. Accuracy evaluation was conducted using MAPE, MSE, and RMSE metrics. The results indicate that the application of SMA without data pre-processing resulted in a high error rate (MAPE 77.25%). However, after implementing pre-processing techniques—including backward interpolation, outlier capping, and iterative smoothing—the accuracy improved significantly, with MAPE values ranging between 20.4% and 21.0%. The developed system provides automated and real-time stock predictions, facilitating more precise, efficient, and structured procurement decision-making. Thus, this system is considered effective in addressing inventory challenges within the F&B sector.

Keywords: inventory, forecasting, moving average, information systems, Food and Beverages.

INTRODUCTION

Raw material inventory is a crucial asset in business operations, especially in the Food and Beverages (F&B) sector, which requires accurate estimation to avoid the risk of excess or shortage of stock (Ma et al., 2025). However, many SMEs still rely on subjective assumptions and conventional recording in managing goods (Lutfi et al., 2025). This manual approach is not only prone to human error and data loss, but it also cannot respond to the uncertainty of dynamic customer demand (Ma et al., 2025). Therefore, the integration of information systems with accurate prediction mechanisms is needed to ensure operational efficiency and customer satisfaction (Chidiebube et al., 2025). A common problem that occurs in raw material stock is stockout and overstock (Rachmawati & Lentari, 2022). Stockout occurs when high demand cannot be met due to limited stock, resulting in lost potential profits for the Company (Buwono et al., 2022). Accumulation of raw material stock occurs due to excessive purchases that do not match existing needs or demand, so if goods are held and do not sell, they are at risk of damage (Gunawan & Setiawan, 2022).

To address this problem, an objective calculation system is required. One of them is the Moving Average method, which is an effective prediction method by taking a group of values from one period to find the average value as a prediction for the upcoming period. This method is effectively used to estimate future raw material stock needs because it is based on certain trend patterns generated from fluctuations in the sales of goods in the previous period. Forecasting serves as a data-based estimation technique aimed at anticipating future events and preventing operational losses (Buwono et al., 2022). The Single Moving Average method is chosen for short-term stock forecasting due to its effectiveness in processing data from the last three to four months to ensure consistent product availability (Muna, 2023). In a study by Ardiana and Loekito (2018), the development of a raw material stock prediction system successfully integrated accurate data processing with tested functionality. Black Box testing results with manual verification showed that the PHP-MySQLi-based system is capable of producing consistent forecasting calculations in line with performance targets (MSE). The development of a web-based information system has become an effective and integrative solution to address problems in inventory management. The use of a web-based platform offers advantages in terms of more flexible data accessibility and ensures information security compared to conventional recording methods. In addition, this system is capable of executing prediction algorithms automatically and in real time (Cahyani & Nudin, 2019). The presence of this technology is expected to assist company management in formulating a more efficient, precise, and structured procurement strategy so that the raw materials provided meet consumer needs and avoid the accumulation of raw materials that causes company losses (Gunawan & Setiawan, 2022).

METHOD

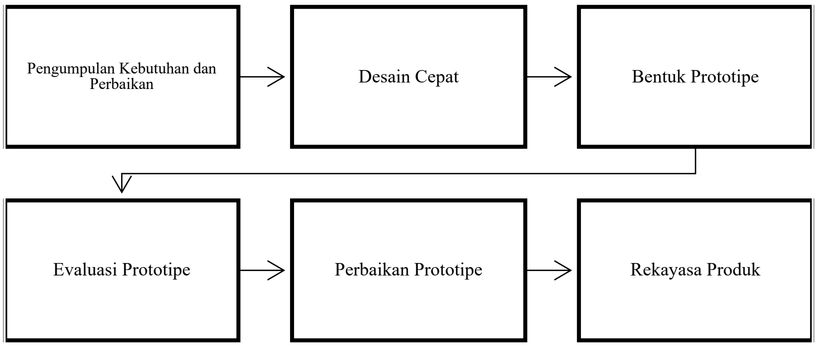


Figure 1. Method Waterfall

Requirements and Data Gathering

This stage focuses on collecting historical datasets as well as identifying the functional requirements of the system. The data used comes from the monthly financial reports of the Benjiro Sushi Lamper branch over a 12-month recording period, including actual usage quantities, item names, and usage history. This data is compiled into a spreadsheet format as the basic material for prototype development. The main target of the system to be built is to be able to forecast stock with minimal error. Maintaining the Integrity of the Specifications

Quick Design

In the quick design stage, system specifications and requirements are directly transformed into technical modeling using Unified Modeling Language (UML) instruments [11]. The UML modeling used in this forecasting system design includes

1. Use Case Diagram, used to map functional interactions between actors (Admin) and the system. This design defines access rights boundaries, where essential features such as uploading CSV data and executing MVA predictions are required to go through an authentication mechanism (Login). Activity Diagram, used to model the system's workflow sequentially. This diagram maps activities from the user uploading historical files, automated pre-processing execution in the background (back-end), to the final calculations visualized on the dashboard
2. Sequence Diagram, is used to visualize the flow of message exchanges between objects based on chronological order. This diagram is specifically designed to map asynchronous communication schemes (request & response) through a JSON API between the user interface and the computation engine.
3. Class Diagram, is used to define the static structure of the database (MySQL) utilized by the system. This diagram maps supporting data entities (such as the *User*, *Raw Material*, and *Prediction* tables), along with their attributes, data types, and relationships between tables.

Building a Prototype

The results of the algorithm and interface design are then implemented into an initial application form (prototype). The system is built using the PHP Laravel framework on the front-end and Python on the back-end to execute mathematical computations of the MVA algorithm automatically on uploaded CSV data. The forecasting engine in this prototype uses the Simple Moving Average (SMA) algorithm with a time range parameter of 4 periods (n=4). This formula is embedded in a Python script to calculate the moving average of raw material usage. The basic formula used is:

$$Ft = \frac{\sum_{i=1}^{n} At}{n} \qquad (1)$$

Description:

Ft = Forecast value for the t-th period (prediction result).
At = Actual data of raw material usage in the previous period.
n = Number of periods used (n=4).

Prototype Evaluation (User Evaluation)

This stage aims to test the performance and accuracy level of the initial prototype that has been built. Testing is conducted by simulating the system's forecasting results against actual usage data. The measurement of the error rate at this evaluation stage is designed using the Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) metrics. To avoid the bias of infinite mathematical calculations due to division by zero, the system applies Conditional MAPE, in which the percentage error is only executed in months that have active transactions (At > 0). The MAPE formula used is:

$$MAPE = \frac{At-Ft}{At} \times 100\% \qquad (2)$$

$$MSE = (At - Ft)^2 \qquad (3)$$

$$RMSE = \sqrt{(At - Ft)^2} \qquad (4)$$

Description:

MAPE: mean absolute percentage error of predictions
MSE: mean squared error of predictions
RMSE: magnitude of error in the original data units
At: actual data value at period t (Actual)
Ft: predicted value at period t (Forecast)
n: number of evaluation periods with actual transactions (At > 0)

The accuracy assessment standards refer to the following table:

Table 1. MAPE Evaluation Standards

MAPE Value Range	Accuracy Interpretation	Description
< 10%	Prediction is highly accurate	Very good
10% – 20%	Prediction is accurate	Good
20% – 50%	Prediction is reasonable	Fair
> 50%	Prediction is inaccurate	Poor

In this initial evaluation, observations were made on raw materials that produced high error values due to gaps in data recording (valued at 0) and extreme fluctuations.

Refining Prototype Results (Refining Prototype)

This stage is an iterative improvement process of the prototype based on the results from the evaluation stage. If the model still produces an error rate (MAPE) above the established tolerance threshold [12], improvements will be made on the data pre-processing side. To suppress errors caused by missing data and extreme fluctuations without manipulating the total actual restaurant stock, three-tiered pre-processing methods are applied, namely:

Backward Allocation. This method is used to address the problem of missing data (Zero-Paradox) by distributing the volume of large batch purchase invoices proportionally backward to the previous empty months. This represents the real customer consumption rate naturally without altering the total annual stock.

Outlier Capping. This method serves as an anomaly filter by using the Z-Score statistical reasonableness limit with the threshold formula (Mean plus 2 times Standard Deviation). Extreme order spikes are trimmed to the maximum limit so that the algorithm does not recommend overstock.

Iterative Data Smoothing. This method iteratively smooths fluctuations (variance) in historical data that deviate significantly from the trend. This process mathematically dampens data volatility so that the MVA algorithm can read trends with precision. Additionally, the evaluation parameters in the enhanced prototype will be expanded using multimetric deviation calculations, namely Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), to ensure more accurate forecasting across the entire period.

The Final Product Implementation (Engineer Product)

After the improvement iteration in the fifth stage successfully reduced the MAPE evaluation values consistently to a more accurate level, the prototype was declared valid and stable. This system was then designated as the final product (deployment) ready to be fully used through an interactive dashboard interface to support decision-making for raw material stock procurement in restaurant management.

RESULTS AND DISCUSSION

Research Results (Prototyping Implementation)

1. **Collection of Requirements and Data**

   In the initial stage, data extraction was carried out from the Financial Statements of Benjiro Sushi Lamper branch for the period January–December. The dataset includes the usage history of hundreds of raw material items, which were then filtered into a spreadsheet (CSV) format. Field data characteristics indicate the presence of a 'Zero-Paradox', namely massive recording gaps (zeros) for certain raw materials as well as sharp fluctuations in orders (high volatility), which pose the main challenge for conventional forecasting algorithms.

Table 2. Sample F&B Raw Dataset (Raw Data)

Item Name	Unit	Month 1	2	3	4	5	6	7	8	9	10	11	12
Ground Beef	Kg	2	2	7	5	5	3	3	3	1	1	3.19	2
Rice	Btl	100	25	0	50	84.4	24.9	22.1	50	25	0	0	25
Black Fungus	Kg	0	0	0	0	0	0	0	4	8	2	2.3	0

2. **Quick Design**

   Based on the defined requirement specifications, the system design is represented in five Unified Modeling Language (UML) models. The following are the modeling results of the architecture and behavior of the Benjiro Sushi forecasting system :

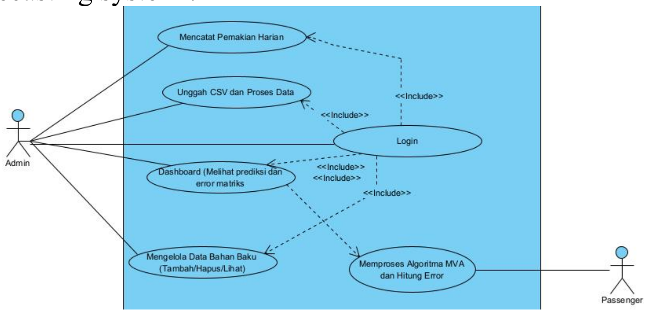


Figure 1. Use Case Diagram

Figure 1 is used to map the interaction between the actor (Admin) and the forecasting system functionality. This design focuses on defining access rights boundaries, where core functionalities such as managing stock history data and executing prediction algorithms are designed with an authentication mechanism (Login). This ensures that all inventory data manipulation processes are protected within a valid authorization framework.

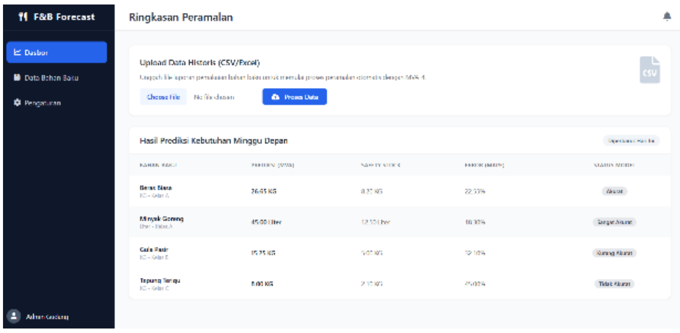
Table 3. Activity Diagram for Data Upload

Actor	Steps	Notes
ADMIN	1. Open Dashboard Page 2. Upload CSV	Initial process initiated by the user.
SYSTEM	3. Receive File 4. Send HTTP POST Request	Bridges the data to the API.
API	5. API Endpoint Receives Request 6. Data Preprocessing 7. Data Smoothing 8. MVA Calculation 9. Error Calculation (MAPE, MSE, RMSE) 10. Send Prediction Results	Core of mathematical processing and forecasting algorithms.
SYSTEM (Decision)	11. Validate Successful Response? - If Yes: Display Results & Success - If No: Display Error Message	Final branching condition before the system completes.

Table 3 above shows the user flow when wanting to make predictions using the web, where CSV data is uploaded and sent to the system to be sent to the Python API for data preprocessing until it is sent back to the system after the calculations are completed.

3. Prototype Development (Build Prototype)

Based on the UML design that has been created, an initial prototype of the F&B inventory management system was built. At this stage, the system is integrated using a MySQL database to store stock history. The interface is developed with a User-Centered Design approach, ensuring that the forecasting graph is placed at the top of the dashboard as priority information for the warehouse admin. The use of the Laravel framework allows the system to handle CRUD (Create, Read, Update, Delete) processes for raw material data with more secure handling. This initial prototype focuses on the system's ability to read uploaded historical CSV data files and pass them to the Python server for processing. As shown in Figure 2 below.



Figures 2. Initial display of the prototype

User Evaluation. At this stage, the initial prototype is handed over to prospective users (Benjiro Sushi Admin) for direct trial use. This evaluation process captures aspects of user experience (UI/UX) and interface interaction. Feedback from users is documented as a basis for improvements in the next iteration. As seen in Table 4 below.

Table 4. Summary of User Feedback on the Initial Prototype

No	Evaluation Aspect	User Comments / Complaints	Follow-up (Prototype Revision)
1	Data Readability	The prediction table is still too dense and monochrome. It is difficult to quickly identify which items require special attention.	Removed the status column and added color coding to MAPE according to calculation results.
2	Responsiveness	When I opened the dashboard using a tablet, the forecasting chart was cut off and did not adjust to the screen.	adjusted the tailwind css grid framework so that the chart becomes responsive.

4. Prototype Refinement (Refining Prototype)

Following user complaints during the evaluation stage, a comprehensive interface improvement was carried out. The system was revised to accommodate more intuitive navigation, the addition of warning color indicators in the status column (Active/Warning/Deadstock), and layout improvements based on a grid to ensure optimal application responsiveness across various devices. Based on complaints about tables being too dense, the system was improved by implementing pagination features and raw material search filters. Data export functionality was also added so that admins can directly print prediction results easily.

5. Final Product Implementation (Engineer Product)

After the interface was refined and the algorithms were optimized on the back-end, the system was implemented fully. The final result is an interactive real-time F&B stock prediction dashboard, ready to support Benjiro Sushi's merchandise procurement operations and inventory management in a computerized manner without visual or computational obstacles. After user evaluation, the final implementation of the interface design is shown in Figure 3 below.

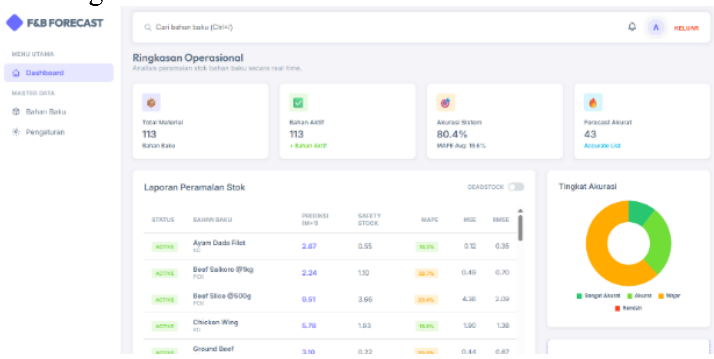


Figure 3. Final result of the interface design implementation

Discussion (Algorithm Analysis and Accuracy)

This section specifically discusses comprehensively the mathematical logic performance of the Moving Average (MVA) algorithm along with its preprocessing methods, which serve as the core computation ("brain") of the inventory forecasting system.

Discussion of the MVA-4 Algorithm

The system uses the Simple Moving Average (SMA) algorithm with a window parameter of n=4. As evidence of the initial computational logic, a sample of Ground Beef raw material is taken to predict the requirements for the fifth month based on the previous four months' data (Jan=2 kg, Feb=2 kg, Mar=7 kg, Apr=5 kg).
Historical data of the previous 4 months:

2 kg, 2 kg, 7 kg, 5 kg. Computation $MVA: F5 = \frac{2+2+7+5}{4} = 4\ kg$ (5)

The initial prototype mathematically succeeded in recommending the number 4 kg as the predicted Ground Beef usage for the next period. The following is a simulation of the calculations in the initial prototype, as shown in Table 5.

Table 5. MVA-4 Computation Simulation of the Initial Prototype (Ground Beef)

Month 1	Month 2	Month 3	Month 4	Forecast (Month 5)
2 kg	2 kg	7 kg	5 kg	4 kg

Discussion of Functional Evaluation (Before Processing)

The initial prototype was evaluated for its mathematical accuracy using the Mean Absolute Percentage Error (MAPE), MSE, and RMSE metrics. Initial testing on raw data showed that the system failed to respond to fluctuating data. As an extreme example, for Ground Beef in the 9th month, the system's prediction was 3.50 kg based on the previous month, but the actual order data dropped sharply to 1 kg. This resulted in a single very large error, namely 250%. Calculate the APE and SE for the 5th month:

$$APE = \frac{5-4}{5} \times 100 \quad (6)$$

$$SE = (At - Ft)^2 = (5-4)^2 = 1 \quad (7)$$

Table 6. Error Calculation Matrix for Ground Beef (Before Preprocessing)

Month	Actual (A)	MVA Prediction (F)	APE (%)	Squared Error (SE)
5	5	4.00	20.00%	1.000
6	3	4.75	58.33%	3.062
7	3	5.00	66.67%	4.000
8	3	4.00	33.33%	1.000
9	1	3.50	250.00%	6.250
10	1	2.50	150.00%	2.250
11	3.19	2.00	37.30%	1.416
12	2	2.04	2.38%	0.002
Total			**618.01%**	**18.980**

In Table 6 above, after obtaining the total error from the entire testing period (8 months), the system calculates the overall average value (Mean) as the final evaluation result:

Average MAPE:

$$MAPE = \frac{Total\ MAPE}{n} = \frac{618.01\%}{8} = 77.25\% \quad (8)$$

Average MSE:

$$MSE = \frac{Total\ SE}{n} = \frac{18.980}{8} = 2.3726 \quad (9)$$

RMSE

$$RMSE = \sqrt{MSE} = \sqrt{2.3726} = 1.5403 \quad (10)$$

The high cumulative error rate is mathematically caused by the weakness of conventional MVA, which is unable to respond to anomaly spikes or zeros in usage history. This results in many raw materials being labeled as 'Inaccurate'.

Table 7. Evaluation Results of the Initial Prototype (Before Preprocessing)

Raw Material	Initial MAPE	Initial MSE	Initial RMSE	Interpretation
Ground Beef	77.25%	2.3726	1.5403	Inaccurate
Rice	50.68%	523.0542	22.8704	Inaccurate
Black Fungus	72.42%	10.5057	3.2412	Inaccurate

Discussion of Data Pre-Processing

Following the high error rate, the system implements three-tiered data pre-processing methods to normalize the dataset. The following is a simulation of calculating the effectiveness proof of the system using a sample of Rice raw materials that had cases of missing data and extreme spikes:

Backward Allocation

a) Initial Data: There was a missing order (0) in March, followed by a large batch purchase in April of 50 bottles/sacks.
b) Calculation: Total orders in April (50) are evenly distributed into the previous empty month plus the current month.

$$\frac{50}{2} = 25 \tag{11}$$

c) Final Result: The order value for March, which was originally 0, and April, which was originally 50, were revised to 25 each. (Note: The system also performs the same operation on the gaps in October-November).

Outlier Capping

a) Initial Data: There was an extreme spike in actual orders in January of 100.
b) Maximum Limit Calculation: From the interpolated data, the system calculates the population mean (total monthly usage divided by 12 = 33.87) and standard deviation:

Step 1: Find the squared difference of each month from the mean.
Example for January: (100 - 33.87)^2 = 4373.1
Example for the month of February: (25 - 33.87)^2 = 78.67
(...and so on until the 12th month)
Step 2: Sum all those squared differences = 9678.89
Step 3: Divide by n-1 (which is 12 - 1 = 11), then take the square root

$$\sigma = \sqrt{\frac{9678.89}{11}} = \sqrt{879.89} = 29.66 \tag{12}$$

Maximum Limit = average + 2 σ = 33.87 + (2 × 29.66) = 33.87 + 59.32 = 93.19 (13)

c) Final Result: Because the order number for January (100) exceeded the reasonable limit, it was reduced to 93.19.

Iterative Data Smoothing

a) Initial Data: The actual value for May jumped to 84.4. Meanwhile, the initial prediction/forecast by the MVA system (based on the average from Jan-Apr) was only 42.05.
b) Calculation (Iteration 1): The system detected a high error difference, so it immediately took the mid-value between the actual data and the prediction.

$$Smoothing = \frac{Actual\,Value + Predicted\,Value}{2} = \frac{84.4+42.05}{2} = \frac{126.45}{2} = 63.22 \tag{14}$$

c) Final Result: The system performs automatic iterative repetition until the value for the month of May successfully tapers from 84.4 to 52.63 so that the error falls within a safe tolerance.
d)

Table 8. Data Value Transformation (Rice) During Preprocessing Stage

Stage	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**
Raw Data (Initial)	100	25	0	50	84.4	24.9	22.1
After Backward Interpolation	100	25	25	25	84.4	24.9	22.1
After Outlier Capping	93.19	25	25	25	84.4	24.9	22.1
After Iterative Smoothing	93.19	25	25	25	52.63	29.73	28.92

Discussion on Improving Final Accuracy

After the raw data undergoes a staged preprocessing phase, the final algorithm accuracy calculation is re-executed using multiple metrics. To visually demonstrate the effectiveness of this method, a comparison of the error rate (MAPE) between the initial prototype (raw data) and the final prototype (clean data) is presented in Figure 4 below:

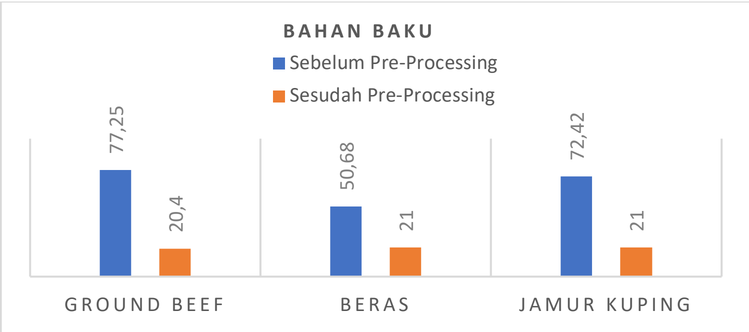


Figure 4. *Comparative graph of materials before and after pre-processing*

Based on the graph above, a very significant decrease in the error percentage is observed. The detailed comparison of MAPE, MSE, and RMSE values is further presented in Table 9 below.

Table 9. Comparison of Final Algorithm Accuracy Evaluation Results

Item Name	Final MAPE	Final MSE	Final RMSE	Interpretation
Ground Beef	20.4%	0.44	0.67	Accurate
Regular Rice @25kg	21%	0.0145	0.1204	Accurate
Black Fungus	21%	0.11	0.3394	Accurate

Table 9 confirms that after hierarchical pre-processing was applied, all raw material samples (including items that previously failed to be calculated/high error) now have a stable accuracy level below the maximum tolerance (30%). The absolute values of MSE and RMSE also dropped drastically, proving that the difference between the estimated volume and the actual field measurement is getting closer. This hybrid forecasting system successfully handles the 'Zero-Paradox' and stock anomalies very well.

CONCLUSION

Based on the stages of system design, implementation, and evaluation that have been carried out, the following conclusions can be drawn:

1. The inventory forecasting system of Benjiro Sushi was successfully built using the Prototyping method. This system implements a hybrid architecture that integrates a PHP Laravel-based user interface with a Python computation engine through JSON API communication.
2. The weakness of the Simple Moving Average (SMA n=4) algorithm in handling empty (Zero-Paradox) and fluctuating data was successfully overcome using three automatic data pre-processing methods, namely: Backward Interpolation, Outlier Trimming, and Repeated Data Smoothing.
3. The application of pre-processing methods has been empirically proven to significantly improve system accuracy. The average error rate (MAPE) was successfully reduced from 77.25% to the range of 20.4% to 21.0%. These results prove that the system is feasible for implementation.

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