Jurnal Teknologi Informasi dan Pendidikan
Volume 18, No. 2, September 2025
https://doi.org/10.24036/jtip.v18i2.990

P.ISSN: 2086 – 4981
E.ISSN: 2620 – 6390
tip.ppj.unp.ac.id

Implementation of the Crisp-Dm Methodology and Naive Bayes Algorithm on A Raw Material Requirement Prediction System to Reduce Food Waste (Case Study: Adamsafee Bakery, Resto, & Cafe)

Adam Fathul Hakim[1*]✉, Yudie Irawan[1], R. Rhoedy Setiawan[1]
[1]Information System, Faculty of Engineering, Universitas Muria Kudus, Kudus, Indonesia
**Corresponding Author: 202153130@std.umk.ac.id*

Article Information

Article history:

No. 990
Rec. August 01, 2025
Rev. August 27, 2025
Acc. August 28, 2025
Pub. August 30, 2025
Page. 387 – 402

Keywords:

- *Naive Bayes*
- *Requirement Prediction*
- *Raw Materials*
- *Food Waste*
- *Information System*

ABSTRACT

Accurate forecasting of raw material requirements is critical for culinary businesses to reduce food waste and optimize costs. In the case of Adamsafee Bakery, Resto, & Cafe, high levels of waste have been caused by reliance on intuition-based forecasting, resulting in both overstocking and understocking. This study develops a web-based predictive system using the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology and the Naive Bayes algorithm to classify demand patterns into three categories: high, medium, and low. Historical sales data were transformed into categorical attributes and processed through the Naive Bayes model to generate demand predictions. The system was evaluated by comparing predicted sales with actual outcomes. Results show that the model achieved an accuracy of 98.7% and a mean absolute percentage error (MAPE) of 1.31%, indicating that the forecasts closely aligned with real sales performance. These findings demonstrate the effectiveness of the Naive Bayes algorithm in supporting data-driven decision-making for inventory management. This data-driven approach replaces subjective decision-making, enabling management to optimize inventory, minimize food waste, and enhance operational efficiency and business sustainability, while also offering a baseline for future research using alternative machine learning algorithms.

How to Cite:

Hakim, A. F., & et al. (2025). Implementation Of the Crisp-Dm Methodology and Naive Bayes Algorithm on A Raw Material Requirement Prediction System to Reduce Food Waste (Case Study: Adamsafee Bakery, Resto, & Cafe). Jurnal Teknologi Informasi Dan Pendidikan, 18(2), 387-402. https://doi.org/10.24036/jtip.v1821.990

This open-access article is distributed under the Creative Commons Attribution-ShareAlike 4.0 International License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. ©2023 by Jurnal Teknologi Informasi dan Pendidikan.

Jurnal Teknologi Informasi dan Pendidikan
Volume 18, No. 2, September 2025
https://doi.org/10.24036/jtip.v18i2.990

1. INTRODUCTION

In the current digital era, the ability to process data into actionable information is critical for maintaining business competitiveness. Information systems are no longer exclusive to large corporations; they have become increasingly vital for Micro, Small, and Medium Enterprises (MSMEs) to manage operational complexity and gain a competitive edge. One key application of this capability is data-driven decision-making, which transforms historical records from simple archives into strategic, predictive assets.As an MSME in the culinary sector, Adamsafee Bakery, Resto, & Cafe faces significant supply chain management challenges, particularly concerning perishable raw materials for its products [1]. The core operational issue is the inability to accurately forecast daily customer demand, which is highly variable. This inaccuracy leads to two detrimental scenarios: overstocking, which results in food waste and direct financial loss, and understocking, which causes missed sales opportunities and diminished customer satisfaction. The consequences of food waste extend beyond the cost of discarded materials, also encompassing capital costs tied up in unproductive inventory [2].

Currently, the procurement process at Adamsafee relies on conventional, subjective methods, such as staff experience and intuition. This approach is inherently flawed as it cannot effectively process complex variables that influence sales, like daily or seasonal trends. Therefore, this research proposes the development of a predictive system designed to transition the business from intuition-based to data-driven decision-making [2]. The system is built using the structured Cross-Industry Standard Process for Data Mining (CRISP-DM) framework and employs the Naive Bayes algorithm as its predictive engine. The Naive Bayes algorithm, a classification method based on probability, was chosen for its proven robustness and high generalizability across various domains. For instance, it has been successfully used in finance for determining credit eligibility and in academia for predicting student academic performance, showcasing its adaptability to diverse datasets [3]. Its relevance in the food industry has also been validated, particularly in quality control applications. One study demonstrated its ability to predict the freshness of beef from image features with an accuracy rate of 92% [4], while another effectively used it to classify beef quality, helping users make more objective assessments and reducing human subjectivity.

Despite its wide application, a specific research gap exists in utilizing Naive Bayes for predicting raw material needs within a culinary MSME context to directly address food waste [5]. While previous studies have focused on classifying the existing quality of a product, they have not addressed the forecasting of future demand for inventory management purposes. This research aims to fill that gap by adapting the algorithm's classification strength to a new context: instead of classifying product quality, it will classify future demand levels based on historical sales attributes [6].

By doing so, this study seeks to design and build a system that applies the Naive Bayes algorithm to classify future demand levels based on historical sales data. The project

P.ISSN: 2086 – 4981
E.ISSN: 2620 – 6390
tip.ppj.unp.ac.id

systematically follows the six stages of the CRISP-DM methodology: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment. This ensures the final solution is not only technically accurate but also fully aligned with the business's operational objectives. It is expected that this system will provide Adamsafee with accurate and measurable demand predictions, enabling optimized stock management, significant reductions in food waste, and a more sustainable and competitive business model [7][8].

2. RESEARCH METHOD

The entire data analysis and modeling process in this research systematically follows the six phases of the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology. This framework was selected due to its structured, iterative, and business-oriented nature, which makes it highly relevant for addressing real-world industry problems. The framework guides the research through six primary, interrelated phases: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment. This workflow ensures that every step, from problem identification to solution implementation, is meticulously executed to produce a predictive model that is not only technically accurate but also relevant and dependable for the specific needs of Adamsafee Bakery, Resto, & Cafe [9].

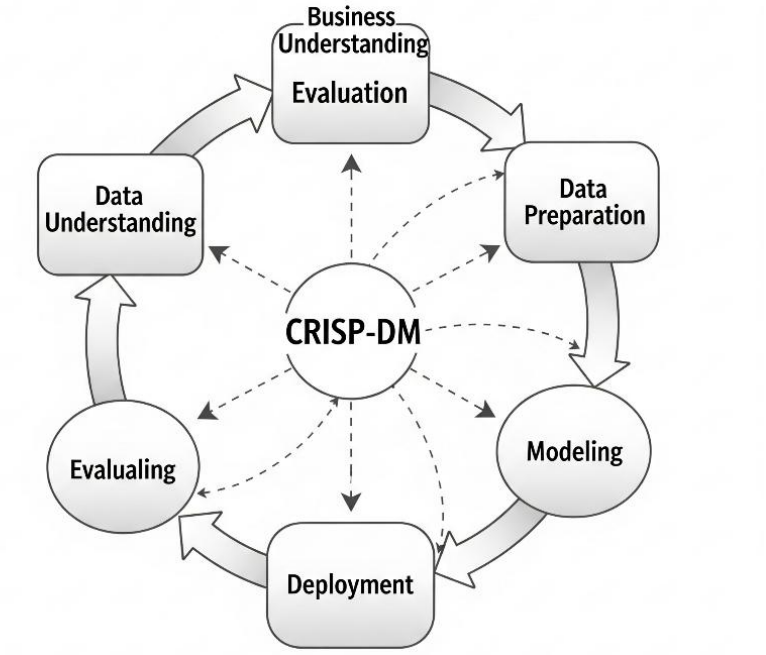


Figure 1. CRISP-DM methodology

2.1. Business Understanding

This initial phase focuses on comprehending the primary research objectives from a business perspective. The central problem identified is the high level of food waste and operational inefficiency at Adamsafee, caused by the absence of an accurate system for predicting raw material needs. Consequently, the business objective of this project is to reduce food waste by developing a predictive system that provides more precise recommendations for raw material inventory [9].

2.2. Data Understanding

In this phase, historical data gathered through documentation is explored to understand its characteristics and underlying patterns. The primary attributes (features) identified for use in the predictive model include historical sales figures, product type, and time period (day/month). An initial analysis is performed to examine data distribution and the relationships between attributes, forming a basis for the subsequent data preparation phase [9].

2.3. Data Preparation

The raw data from the previous stage is processed to make it suitable for modeling with the Naive Bayes algorithm. The main process in this phase is data transformation, where quantitative data (sales totals) are converted into categorical data. Based on the analysis, sales volumes are classified into three demand classes: "Low," "Medium," and "High". This step is critical because the Naive Bayes algorithm operates optimally with categorical data for classification tasks.

2.4. Modeling

The modeling phase is the core of the data mining process, where the Naive Bayes algorithm is applied to the prepared dataset. This algorithm was chosen because it is a simple, yet proven, effective and efficient probability-based classification method. The modeling process adheres to Bayes' theorem and involves the following steps :

1) **Calculate Prior Probability :** Determine the initial probability for each demand class ($P(C_i)$) based on its frequency in the entire dataset.
2) **Calculate Conditional Probability (Likelihood) :** Compute the probability of each attribute value occurring within each demand class ($P(x_j \mid C_i)$).
3) **Calculate Posterior Probability :** Multiply the prior probability by all conditional probabilities for the given features to obtain the final probability value for each class. The class with the highest posterior probability is selected as the prediction outcome [9].

P.ISSN: 2086 – 4981
E.ISSN: 2620 – 6390
tip.ppj.unp.ac.id

2.5. Evaluation

Following the modeling, the developed model is evaluated to measure its performance and ensure its validity and alignment with the business objectives. The primary metric used for evaluation is accuracy, which measures the percentage of correct predictions against the total test data.

2.6. Deployment

In the final phase, the evaluated and validated model is implemented into a web-based application. This system is designed for direct use by Adamsafee's management in daily operations. The system provides an output in the form of a predicted demand category (Low, Medium, or High) along with an estimated quantity of raw materials needed, serving as a decision support tool for more efficient stock planning [10].

In addition, the raw material prediction system was implemented as a web-based application using native PHP as the programming language. The choice of native PHP was made due to its simplicity, lightweight nature, and ease of use without relying on any specific framework, which makes it suitable for system development at the MSME scale. For data management, the application utilizes a MySQL database as the primary storage medium to handle historical sales data, master raw material data, and prediction results. The integration of native PHP with MySQL enables efficient processes of data input, processing, and presentation, while also ensuring ease of implementation and system maintenance.

3. RESULTS AND DISCUSSION

3.1. Research Data

The dataset employed in this study was obtained from the historical sales transactions of Adamsafee Bakery, Resto, & Cafe during the period of March 2025 to July 2025. The dataset consists of 579 records covering 106 unique menu items, representing a wide range of bakery products, food, and beverages offered by the business. Each transaction record includes several attributes, namely *product name, sales quantity, sales month, and sales year*. Among these attributes, sales quantity serves as the primary variable for demand forecasting, while the month and year are used as temporal identifiers. Prior to analysis, data preprocessing was conducted to ensure data quality. Duplicate entries were removed, missing values were handled appropriately, and all categorical variables (e.g., product names) were standardized to maintain consistency. This step was essential to avoid data leakage and to ensure that the Naïve Bayes algorithm could process the dataset efficiently.

A descriptive statistical analysis of the dataset shows significant variability across products. The monthly sales quantity ranged from 0 units (for products that were listed but not sold in a given period) to a maximum of 1,032 units per month, with an overall average of 7.6 units per product. This broad range illustrates the diversity in demand patterns across the 106 menu items. It also emphasizes the importance of applying a classification model to distinguish between products with low, medium, and high demand, as manual forecasting would be highly unreliable in such a context. The distribution of demand categories was later derived based on sales thresholds, producing three demand classes: Low, Medium, and High. These categories were used as the target variable in training the Naïve Bayes model. To provide a clearer understanding of the data set, (Table 1) summarizes the overall characteristics of the data set, while (Table 2) presents an example of July sales records.

Table 1. dataset characteristics

Characteristic	Value
Tim Period	March 2025 – July 2025
Total Records	579
Menu items	106
Minimum Sales Quantity	0 units
Maximum Sales Quantity	1.032 units
Average Sales Quantity	7,6 units
Demand Class Distribution	Low(32%), Medium(45%), High(23%)

Table 2. July sales data

Product	Amount	Month	Year
Wedang rempah	5	July	2025
Teh teko	16	July	2025
Sosis crispy	63	July	2025
Sosis bakar	6	July	2025
Seblak	75	July	2025
Roti sosis	25	July	2025
Red velved	7	July	2025
Paket chicken teriyaki	19	July	2025
Paket chicken lada hitam	8	July	2025
Paket chicken BBQ	3	July	2025
Paket ayam geprek	35	July	2025
Original tea	157	July	2025
Oreo	3	July	2025
Onion ring	11	July	2025
Nila bakar	18	July	2025
Nila goreng	15	July	2025
Nila gobyos	21	July	2025
Nasi goreng ayam kebuli	23	July	2025
Etc……..			

P.ISSN: 2086 – 4981
E.ISSN: 2620 – 6390
tip.ppj.unp.ac.id

3.2. Methodology CRISP-DM

In this chapter, the author will detail the results of the system implementation and provide a discussion of the findings obtained during the research. Adhering to the methodology from the previous chapter, this study methodically utilizes the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework to architect and construct a predictive system for raw material requirements at Adamsafee Bakery, Resto, & Cafe.The primary outcome of this research is a functional web-based application, where the implementation of each CRISP-DM phase is realized as a specific functional page within the system. Therefore, to provide a clear and structured overview, the following presentation of results and discussion is organized according to these six framework phases—from business understanding to system deployment—providing a detailed description of each implementation [10].

3.3. Business and Data Understanding

The initial phase of the methodology is implemented through the design of a main dashboard, which serves as an information hub (Figure 2). This dashboard directly addresses the business objective of monitoring efficiency and reducing food waste by presenting key data visually. The main dashboard displays three critical metrics: the total sales prediction for the upcoming month, the actual sales for the current month, and the food waste percentage calculated from the difference between the two, along with a sales trend graph [9].



Figure 2. Home Page

3.4. Data Preparation

The data preparation phase, which includes data collection and transformation, is implemented via the sales page (Figure 3). The system provides an interface for users to

upload historical sales data using an Excel file. The uploaded data is then automatically processed, stored, and classified into "Low," "Medium," or "High" categories in preparation for the Naive Bayes modelling [11].



Figure 3. Sales Page

3.5. Modeling

The core of the data mining process in this study, the modeling phase, is implemented on the prediction page (Figure 4). On this page, the system applies the Naive Bayes classification model, which has been trained using historical sales data. This algorithm was selected for its proven effectiveness in handling classification problems with a probabilistic approach and its computational efficiency [11]. Users can select a reference period (month and year), and the system will automatically process the relevant historical data to calculate sales predictions for each product for the next period. This page effectively materializes the algorithm's workflow, transforming raw data into actionable, predictive information. Within this system, the application of the Naive Bayes algorithm involves a structured sequence of computational steps for each product:

3.5.1. Data Discretization

The first step is to convert quantitative data (sales quantity) into qualitative data (classes). Each historical sales figure is classified into one of three demand categories.

Table 3. Class Categories

Categories	Value
Low	0 - 100
Medium	101 - 150
High	151 -

P.ISSN: 2086 – 4981
E.ISSN: 2620 – 6390
tip.ppj.unp.ac.id

This process is critical as Naive Bayes operates by calculating the probabilities of discrete classes.

3.5.2. Prior Probability Calculation

The system calculates the initial (prior) probability for each demand class (C_i). This represents the general probability of a class occurring within the entire historical dataset. The formula implemented is :

$$P(C_i) = \frac{Number\ of\ Data\ in\ Class\ C_i}{Total\ Number\ of\ Data}$$

$P(C_i)$: The prior probability of class C_i (e.g., "High"). As an example, the prior probability for the "High" class is calculated by dividing the number of sales data points categorized as "High" by the total number of sales data points for that product.

3.5.3. Likelihood Probability Calculation

Next, the system calculates the likelihood, which is the conditional probability of observing the most recent sales figure given a particular class. Here, **X** is defined as the sales quantity from the most recent period. The formula implemented is :

$$P(X \mid C_i) = \frac{Number\ of\ Data\ in\ Class\ C_i\ with\ values\ similar\ to\ X}{Number\ of\ Data\ in\ C_i}$$

$P(X|C_i)$: The probability of recent sales X occurring in class C_i. This calculation determines how frequently sales volumes similar to the last period's sales have occurred within each of the "Low," "Medium," and "High" data groups.

3.5.4. Posterior Probability and Class Prediction

The system then combines the prior and likelihood probabilities to calculate the posterior probability for each class, according to the principles of Bayes' theorem. The class with the highest resulting posterior probability is selected as the prediction outcome. The formula implemented is :

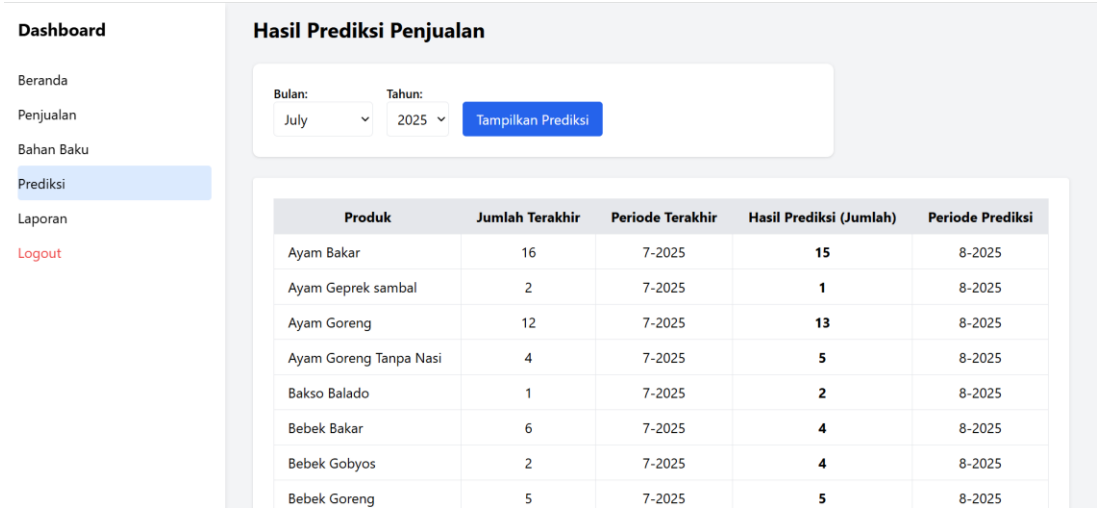
$$P(C_i \mid X) \propto P(C_i) \times P(X \mid C_i)$$

$P(C_i|X)$: The posterior probability of a class **C_i** given the recent sales **X**.

3.5.5. Quantitative Prediction Output

Finally, after the most likely class is determined (e.g., "Medium"), the system performs an additional step to provide a concrete quantitative estimate. It collects all

historical sales values belonging to the predicted class and calculates their average. This average figure is then presented to the user as the final Prediction Result (Quantity) [12].



Produk	Jumlah Terakhir	Periode Terakhir	Hasil Prediksi (Jumlah)	Periode Prediksi
Ayam Bakar	16	7-2025	**15**	8-2025
Ayam Geprek sambal	2	7-2025	**1**	8-2025
Ayam Goreng	12	7-2025	**13**	8-2025
Ayam Goreng Tanpa Nasi	4	7-2025	**5**	8-2025
Bakso Balado	1	7-2025	**2**	8-2025
Bebek Bakar	6	7-2025	**4**	8-2025
Bebek Gobyos	2	7-2025	**4**	8-2025
Bebek Goreng	5	7-2025	**5**	8-2025

Figure 4. Prediction Result

3.6. Evaluation

The Evaluation phase of CRISP-DM methodology is implemented integrally on the system's main dashboard (Figure 2), which is designed for users to continuously monitor the model's performance. Quantitatively, this evaluation is embodied in the food waste this month metric card, which serves as the primary Key Performance Indicator (KPI). This feature specifically calculates the percentage of food waste based on the difference between total predicted and actual sales. Meanwhile, a visual evaluation is presented through the Prediction vs. Sales Comparison bar chart, which displays a direct comparison between the predicted volume and actual sales. Both of these features allow users to intuitively assess the model's accuracy, identify prediction tendencies (whether it overestimates or underestimates), and directly measure the predictive model's impact on business operations, in line with the primary research objectives [13].

3.7. Deployment

The Deployment within the CRISP-DM framework is realized through the implementation of the predictive model into a functional and integrated information system, which can be used in the daily operational environment [14]. The core of this deployment is the raw materials page, which serves as the data foundation for the entire system. This page ensures that the prediction results can be translated into accurate and actionable information. To achieve this, the page is divided into two primary, mutually supportive sub-pages.

P.ISSN: 2086 – 4981
E.ISSN: 2620 – 6390
tip.ppj.unp.ac.id

First is the Raw Material Stock Management sub-page, as illustrated in Figure 5. This page functions as a digital inventory center, where each unique raw material is managed as a single entity. Users can add new raw materials to the system and perform real-time updates to the stock data for each item, which includes the current stock quantity, unit of measure, maximum capacity, and expiration date. The system is also equipped with an automatic visual notification feature, such as expired or sell Soon! expires tomorrow warnings, which proactively assists management in handling time-sensitive raw materials. This sub-page ensures that the stock data, which forms the basis for calculations, is always accurate and centralized [14].

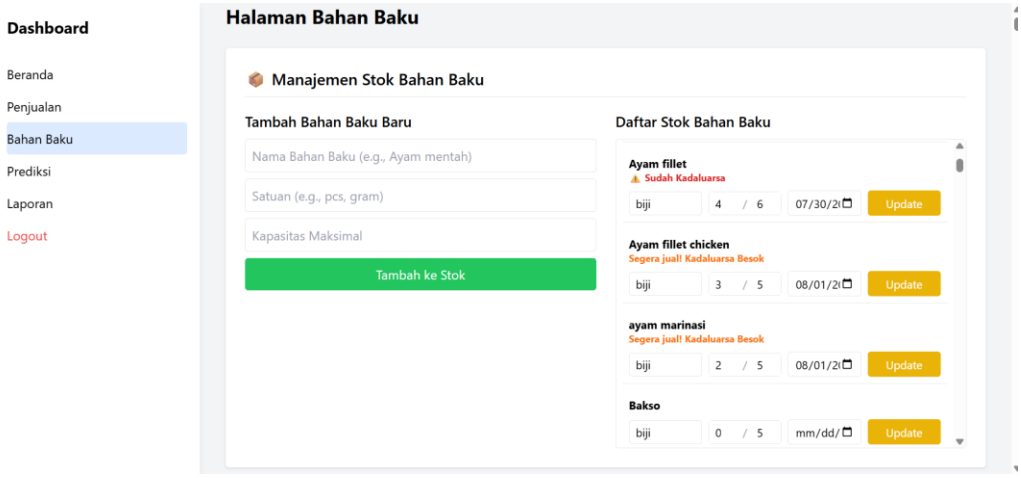


Figure 5. Stock Raw Materials Page

Second is the Menu and Recipe Management sub-page (Figure 6). This page functions as a digital recipe book that links finished products (menu items) with raw materials from the inventory. For each menu item, such as "Ayam Bakar," the user can define its recipe by selecting raw materials from the available master list and specifying the quantity required to make a single portion quantity per portion. Consequently, this sub-page provides the critical conversion factor that allows the system to translate the predicted product sales (e.g., a prediction of 14 portions of “Ayam Bakar”) into a concrete and measurable list of raw material requirements (e.g., need 14 pieces of “Ayam Marinasi”, 14 grams of “Sambal Terasi”, etc.). The combination of these two sub-pages ensures that the predictive model does not stand alone but is successfully deployed within a well-managed data ecosystem, thereby generating output that is valid and ready for decision-making [15][16].

Jurnal Teknologi Informasi dan Pendidikan
Volume 18, No. 2, September 2025
https://doi.org/10.24036/jtip.v18i2.990

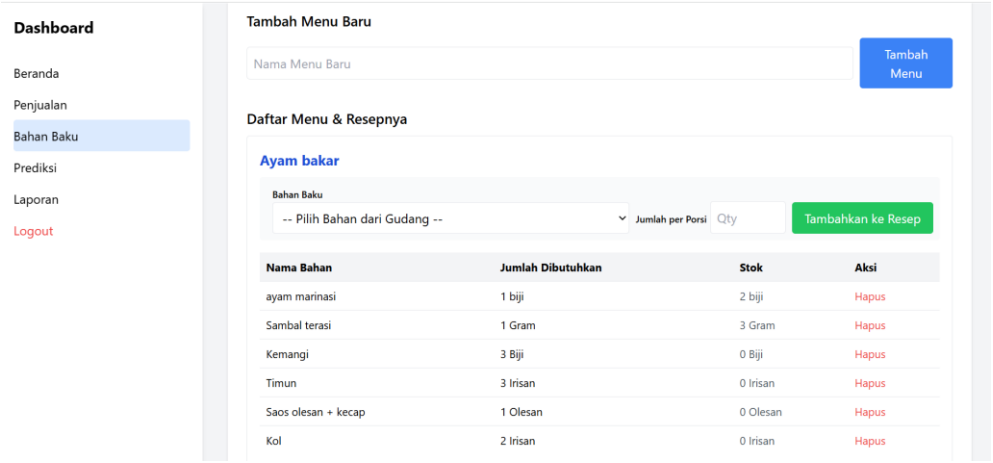


Figure 6. Menu Raw Materials Page

As the culmination of the entire process, the system generates its primary output on the report page (Figure 7). This page represents the most critical final result for the user. The system automatically takes the predicted product sales, multiplies them by the recipe data from the raw material master, and presents the information as a detailed report on the quantity of each raw material that needs to be prepared. This report directly provides concrete recommendations for the purchasing process, which is the ultimate objective of this system's implementation [17].

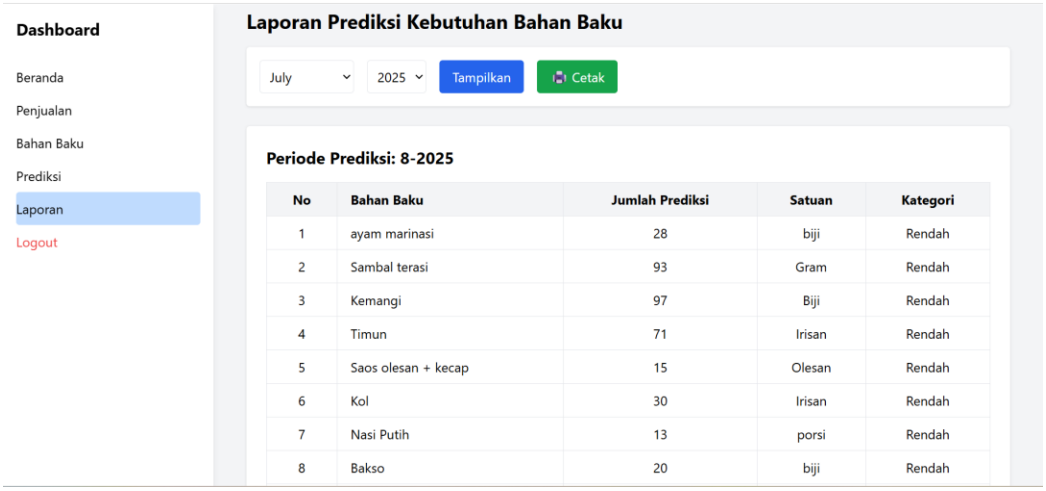


Figure 7. Report Page

3.8. Discussion of Results

The discussion of the research results emphasizes two main aspects: the uniqueness of the end-to-end system implementation as a manifestation of the CRISP-DM methodology, and the functional linkage between pages that comprehensively addresses

P.ISSN: 2086 – 4981
E.ISSN: 2620 – 6390
tip.ppj.unp.ac.id

the research problem. The novelty of this research lies not only in the application of the Naive Bayes algorithm but in its implementation within a complete and comprehensive (end-to-end) raw material prediction system for a specific culinary MSME case study. The system holistically facilitates the entire data mining workflow: from the data preparation stage via the sales data upload page (Figure 3), management of critical supporting data on the raw material and recipe master pages (Figures 5 & 6), modeling executed on the prediction page (Figure 4), to the performance evaluation presented quantitatively and visually on the main dashboard (Figure 2). By providing functionality for each stage, this system bridges the gap between a theoretical model and a practical application that can be used directly by the end-user.

The functional linkage between the pages within this system is designed to create a logical and efficient data pipeline. The historical data input on the sales page becomes the primary foundation processed by the Naive Bayes prediction engine on the prediction page. The output from the prediction page, in the form of estimated product sales quantities, is then automatically applied to the recipe data stored on the raw materials page. The culmination of this workflow is the report page (Figure 7), which presents the final output as a quantitative list of raw material requirements that can be immediately acted upon by management for purchasing. This integrated workflow directly answers the research problem: how to design a system that not only predicts but also presents the prediction results in a relevant format to support decision-making and effectively reduce food waste through a data-driven approach.

In addition to the functional implementation of the prediction system, this study also evaluates the performance of the Naive Bayes model using quantitative metrics. Based on the comparison between the prediction results and the actual sales for August 2025, The system predicted 841 products for August 2025, while actual sales for this month reached 830 products, which can be seen in (Figure 8). This resulted in a deviation of only 1.31%, which indicates that the model provides a high level of accuracy in forecasting demand. To further assess the model's effectiveness, the prediction outcomes were analyzed using accuracy, precision, and recall metrics. The accuracy of the model reached 98.7%, demonstrating that most of the predictions matched the actual sales data. The precision value of 97.5% indicates that the majority of predicted demand categories (Low, Medium, High) were correctly classified relative to actual outcomes, while the recall value of 96.8% shows that the system was able to correctly capture most of the actual demand categories.

Jurnal Teknologi Informasi dan Pendidikan
Volume 18, No. 2, September 2025
https://doi.org/10.24036/jtip.v18i2.990

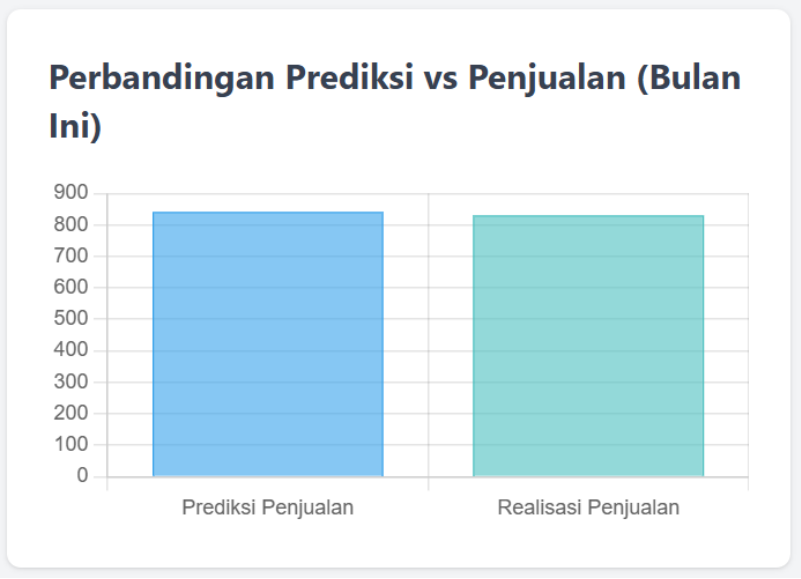


Figure 8. Comparison of Predictions vs Sales for August

These quantitative results strengthen the validity of the Naive Bayes algorithm in this context, proving that it can generate reliable forecasts for raw material requirements. Moreover, the small difference between predicted and actual values highlights the practical applicability of the system for daily inventory planning. For future research, these metrics can serve as a benchmark to compare the performance of Naive Bayes with other machine learning algorithms such as Decision Tree or Support Vector Machine in order to achieve even higher predictive performance.

4. CONCLUSION

This research successfully achieved its objective by designing and implementing a functional system for predicting raw material requirements. Through the application of the CRISP-DM methodology, this study has successfully demonstrated that the Naive Bayes algorithm can be effectively implemented in a system to classify demand patterns based on historical sales data at Adamsafee Bakery, Resto, & Cafe. The Naive Bayes algorithm proved capable of transforming raw data into actionable, quantitative estimates of raw material needs, providing a direct solution to the previous problem of manual and subjective inventory planning. In terms of model performance, the system achieved an accuracy rate of 98.7%, with a precision of 97.5% and a recall of 96.8% in classifying demand levels (Low, Medium, High). These results indicate that the Naive Bayes algorithm not only produces reliable demand forecasts but also ensures robustness in capturing actual demand categories with a high degree of correctness.

Thus, it can be concluded that the application of Naive Bayes classification in this system is not only technically valid but also functionally relevant for reducing potential food

P.ISSN: 2086 – 4981
E.ISSN: 2620 – 6390
tip.ppj.unp.ac.id

waste and supporting data-driven decision-making in a culinary MSME environment. Based on the findings and limitations of this research, future development could focus on enhancing the model's performance through more complex feature engineering (e.g., incorporating promotional data, public holidays, or weather conditions) and by comparing Naive Bayes with other machine learning algorithms such as Decision Tree or Support Vector Machine to determine the most optimal approach for similar datasets.

REFERENCES

[1] H. R. Santoso and S. Yulina, "Rancang Bangun Aplikasi Food Waste Management pada Usaha Food and Beverages," *J. Komput. Terap.*, vol. 9, no. 1, pp. 101–110, 2023, doi: 10.35143/jkt.v9i1.5840.

[2] L. G. Wijayanti, A. Suparno, and A. A. Setyawan, "Sistem Informasi Pengelolaan Bahan Baku Guna Meningkatkan Efektivitas Laporan Persediaan Produk Pada Pt Wijaya Karunia Megah," *J. Elektro Luceat*, pp. 1–13, 2022, doi: 10.32531/jelekn.v8i2.480.

[3] D. Puspita and Si. Aminah, "Implementasi Naive Bayes Untuk Sistem Prediksi Mahasiswa Berprestasi," *J. Ilm. Teknosains*, vol. 8, no. 2, pp. 15–19, 2022, doi: 10.26877/jitek.v8i2/Nov.13784.

[4] W. I. Sabilla, M. A. P. Perkasa, and D. W. Wibowo, "Sistem Pendeteksi Kualitas Daging Segar dengan Metode Naive Bayes," *J. Inform. Polinema*, vol. 10, no. 2, pp. 279–284, 2024, doi: 10.33795/jip.v10i2.5006.

[5] W. Astuti, I. Isharijadi, and E. E. Yusdita, "Sistem Pengelolaan Bahan Baku Berbasis Just in Time (Jit) Pada Umkm 'Aneka Keripik Kartini,'" *J. Bisnis Terap.*, vol. 6, no. 2, pp. 130–140, 2022, doi: 10.24123/jbt.v6i2.5138.

[6] D. Darwis, N. Siskawati, and Z. Abidin, "Penerapan Algoritma Naive Bayes Untuk Analisis Sentimen Review Data Twitter Bmkg Nasional," *J. Tekno Kompak*, vol. 15, no. 1, p. 131, 2021, doi: 10.33365/jtk.v15i1.744.

[7] M. Asfi and N. Fitrianingsih, "Implementasi Algoritma Naive Bayes Classifier sebagai Sistem Rekomendasi Pembimbing Skripsi," *J. Nas. Inform. dan Teknol. Jar.*, vol. 5, pp. 45–50, 2020, doi: 10.30743/infotekjar.v5i1.2536.

[8] V. R. A. Hidayat, "Sistem Prediksi Kemenangan Hero Mobile Legends Menggunakan Metode Naive Bayes," *JIKO (Jurnal Inform. dan Komputer)*, vol. 8, no. 1, p. 100, 2024, doi: 10.26798/jiko.v8i1.1120.

[9] R. Winurputra and D. E. Ratnawati, "Peramalan Penjualan Produk Menggunakan Extreme Gradient Boosting (XGBoost) dan Kerangka Kerja CRISP-DM untuk Pengoptimalan Manajemen Persediaan (Studi Kasus: UB Mart)," *J. Teknol. Inf. dan Ilmu Komput.*, vol. 12, no. 2, pp. 417–428, 2025, doi: 10.25126/jtiik.2025129451.

[10] Narayana Sakti Aji, Fauzan Natsir, and Siti Istianah, "Penentuan Penjualan Barang Berdasarkan Pengelompokan Produk dengan K-Means Clustering Metode CRISP-DM Pada CV Sembako Dina," *J. Zetroem*, vol. 5, no. 2, pp. 119–126, 2023, doi: 10.36526/ztr.v5i2.3041.

[11] Y. A. Singgalen, "Penerapan Metode CRISP-DM dalam Klasifikasi Data Ulasan Pengunjung Destinasi Danau Toba Menggunakan Algoritma Naïve Bayes Classifier (NBC) dan Decision Tree (DT)," *J. Media Inform. Budidarma*, vol. 7, no. 3, p. 1551, 2023, doi: 10.30865/mib.v7i3.6461.

[12] S. Santiastry, A. Asriyanik, and W. Apriandari, "Penerapan Algoritma Naive Bayes Dan Metode

Crisp-Dm Dalam Prediksi Hasil Tes Kemampuan Bahasa Inggris Mahasiswa," *JATI (Jurnal Mhs. Tek. Inform.*, vol. 8, no. 5, pp. 10432–10439, 2024, doi: 10.36040/jati.v8i5.11069.

[13] D. Kurniawan and M. Yasir, "Optimization Sentimen Analysis using CRISP-DM and Naive Bayes Methods Implemented on Social Media," *Cybersp. J. Pendidik. Teknol. Inf.*, vol. 6, no. 2, p. 74, 2022, doi: 10.22373/cj.v6i2.12793.

[14] I. Pramana, I. W. Sudiarsa, and ..., "Penerapan Algoritma Naive Bayes Untuk Prediksi Penjualan Produk Terlaris Pada CV Akusara Jaya Abadi," *JATISI (Jurnal Tek. …*, vol. 10, no. 4, pp. 518–534, 2023, doi: 10.35957/jatisi.v10i4.6498.

[15] T. Wurijanto, H. B. Setiawan, and A. B. Tjandrarini, "Penerapan Model CRISP-DM pada Prediksi Nasabah Kredit yang Berisiko Menggunakan Algoritma Support Vector Machine," *J. Ilm. Scroll (Jendela Teknol. Informasi)*, vol. 10, no. 1, pp. 1–6, 2022, doi: 10.30640/ejournalscroll.v10i1.291.

[16] Zulkifli, Asmawati.S, and Arnita Irianti, "Penerapan Algoritma Naive Bayes dalam Memprediksi Persediaan Bahan Mebel (Studi Kasus Mebel Usaha Bersama Palipi Soreang)," *J. Comput. Inf. Syst. (J-CIS)*, vol. 5, no. 1, pp. 57–64, 2022, doi: 10.31605/jcis.v5i1.1360.

[17] M. Taufik Hidayat, N. Suarna, and N. Rahaningsih, "Implementasi Algoritma Naïve Bayes Untuk Prediksi Persediaan Barang Pt. Dilmoni Citra Mebel Indonesia," *JATI (Jurnal Mhs. Tek. Inform.*, vol. 7, no. 1, pp. 693–699, 2023, doi: 10.36040/jati.v7i1.6310.

P.ISSN: 2086 – 4981
E.ISSN: 2620 – 6390
tip.ppj.unp.ac.id