

DAYANANDA SAGAR UNIVERSITY

Devarakaggalahalli, Harohalli, Kanakapura Road, Ramanagara Dist – 562 112.



**SCHOOL OF
ENGINEERING**

Bachelor of Technology in COMPUTER SCIENCE AND ENGINEERING

Power BI and RapidMiner (4th Semester Skill Enhancement Course) Project Report

Cafeteria Demand Waste Tracker

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**DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING,
SCHOOL OF ENGINEERING
DAYANANDA SAGAR UNIVERSITY
(2024-2025)**



School of Engineering
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This is to certify that the Project titled "**Cafeteria Demand Waste Tracker**" is carried out under **Power BI and RapidMiner** (4th Semester Skill Enhancement) Course by **Shruthi Mohan (ENG23CS0186)**, **Abhinava Sajeev(ENG23CS0003)**, **Aishwarya B S (ENG23CS0251)**, **T M Navya Shree(ENG23CS0205)** bonafide students of Bachelor of Technology in Computer Science and Engineering at the School of Engineering, Dayananda Sagar University, Bangalore in partial fulfilment for the award of degree in Bachelor of Technology in Computer Science and Engineering, during the year **2024-2025**.

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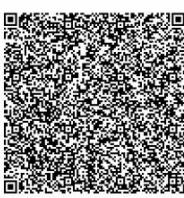
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First, we take this opportunity to express our sincere gratitude to School of Engineering & Technology, Dayananda Sagar University for providing us with a great opportunity to pursue our Bachelor's degree in this institution.

We would like to thank **Dr. Uday Kumar Reddy K R, Dean, School of Engineering & Technology, Dayananda Sagar University** for his constant encouragement and expert advice. It is a matter of immense pleasure to express our sincere thanks to **Dr. Girisha G S, Chairman, Department of Computer Science, and Engineering, Dayananda Sagar University**, for providing the right academic guidance that made our task possible.

We would like to thank our guides **Dr. Basavaraj N Hiremath, Professor, Dr. Savitha Hiremath, Associate Professor and Prof. Muthu Bala N, Assistant Professor, Dept. of Computer Science and Engineering, Dayananda Sagar University**, for sparing his/her valuable time to extend help in every step of our Special Topic 1, which paved the way for smooth progress and the fruitful culmination of the project.

We are also grateful to our family and friends who provided us with every requirement throughout the course. We would like to thank one and all who directly or indirectly helped us in completing the Project under **Power BI and RapidMiner** (4th Semester SEC) Course.

DECLARATION

We, **Shruthi Mohan (ENG23CS0186)**, **Abhinava Sajeev(ENG23CS0003)**, **Aishwarya B S (ENG23CS0251)**, **T M Navya Shree(ENG23CS0205)**, are students of the Fourth semester B.Tech in **Computer Science and Engineering**, at School of Engineering, **Dayananda Sagar University**, hereby declare that the project under **Power BI and RapidMiner** (4th Semester Skill Enhancement) Course titled "**Cafeteria Demand Waste Tracker**" has been carried out by us and submitted in partial fulfillment for the award of degree in **Bachelor of Technology in Computer Science and Engineering** during the academic year **2024-2025**.

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NOMENCLATURE USED

Power BI	Power Business Intelligence
KPI	Key Performance Indicator
Waste(kg)	Waste in kilograms

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ABSTRACT

In institutional and commercial cafeterias, food wastage due to inaccurate demand forecasting remains a persistent issue, leading to significant economic and environmental impacts. This project presents a comprehensive solution for tracking and minimizing cafeteria food waste by leveraging data analytics and visualization tools—Power BI for interactive dashboards and RapidMiner for predictive modelling.

Historical data on meal preferences, footfall, and wastage patterns were collected and processed to build a demand forecasting model using RapidMiner. The model utilizes machine learning algorithms to predict daily food demand based on factors such as weekday trends, seasonal variations, and event schedules. These predictions are then visualized through dynamic and user-friendly dashboards in Power BI, enabling cafeteria managers to make data-driven decisions regarding food preparation.

The system not only helps in optimizing inventory and reducing food waste but also contributes to sustainable operational practices. The integration of real-time tracking and historical trend analysis provides actionable insights that enhance forecasting accuracy and operational efficiency.

This project demonstrates the potential of combining machine learning with business intelligence tools to address real-world sustainability challenges in food service management.

CHAPTER 1 INTRODUCTION

In the food service industry, particularly within institutional cafeterias such as those in universities, offices, and hospitals, managing food waste is a persistent and complex challenge. Despite best efforts, a significant proportion of prepared food is discarded daily due to overproduction and unpredictable demand. This not only leads to economic losses but also raises serious concerns about environmental sustainability, ethical food management, and resource utilization.

To address these issues, the Cafeteria Demand Waste Tracker project integrates predictive analytics using RapidMiner and interactive visualization through Power BI. By leveraging historical and real-time data, the system is designed to forecast daily food waste (in kilograms) based on a variety of influential factors including meal type, food item, inventory usage, weather conditions, and customer feedback. The ultimate goal is to enable cafeteria managers and decision-makers to anticipate demand more accurately, plan meals more efficiently, and minimize food waste without compromising service quality.

- **1.1 Problem Background**

Cafeteria operations often rely on static historical averages or manual estimation techniques to determine the quantity of food to prepare each day. However, these traditional approaches fail to account for dynamic and context-sensitive variables that significantly influence consumption patterns. For instance, weather conditions can affect appetite and turnout; customer feedback can highlight dissatisfaction with certain dishes, and inventory fluctuations can impact meal preparation decisions.

The lack of a responsive, data-driven forecasting model often results in over-preparation, leading to an excess of unconsumed food. On the other hand, underestimation can result in shortages and poor customer experiences. Moreover, the food that is discarded contributes to carbon emissions, wasted water and energy, and increased disposal costs. Addressing these problems requires a smart, adaptive system that can learn from complex datasets and make informed predictions to guide meal planning and resource allocation.

- **1.2 Project Objective**

The primary objective of this project is to develop a predictive model capable of estimating the amount of food waste generated per meal on a daily basis. This model will be built using RapidMiner's machine learning capabilities, which allow for the analysis of large and diverse datasets. Key variables such as meal type, specific food items, inventory used, prevailing weather conditions, and qualitative customer feedback will be used as inputs to train and test the model.

Once the model is developed, its outputs will be visualized through Power BI dashboards, allowing users to interact with the data and uncover trends, patterns, and anomalies. These visualizations will support better decision-making by providing real-time insights into waste generation and enabling cafeteria staff to proactively adjust their operations. By implementing this solution, the project aims to achieve measurable reductions in food waste, enhance operational efficiency, and contribute to more sustainable food management practices.

CHAPTER 2 PROBLEM STATEMENT

Predict Daily Waste to Improve Efficiency ---"Develop a predictive model that estimates food waste (in kg) for a given meal based on factors like meal type, food item, inventory used, weather, and customer feedback, with the goal of minimizing food waste in the cafeteria."

- **Detailed Explanation**

In institutional cafeterias, food waste is a recurring issue caused primarily by inaccurate meal planning and demand forecasting. Cafeterias often prepare more food than needed, leading to excess waste, increased costs, and environmental harm. Traditional planning methods fail to consider important variables like meal type, food item popularity, weather, inventory levels, and customer feedback, which all influence daily consumption patterns.

1. Meal Type: Different types of meals (breakfast, lunch, dinner) have varying levels of demand.
2. Food Item: Certain food items are more popular or seasonal, affecting how much gets consumed.
3. Inventory Used: The availability and quantity of ingredients can impact meal variety and portion sizes.
4. Weather Conditions: Weather can influence customer turnout and appetite. For instance, rainy or hot days may reduce cafeteria traffic.
5. Customer Feedback: Regular input from customers can reflect satisfaction with meals, guiding future planning and reducing the risk of preparing unpopular dishes.

The objective of this project is to build a predictive model that estimates daily food waste (in kilograms) using these key factors.

CHAPTER 3 DATASET DESCRIPTION

The dataset used for this project captures historical records of food preparation, consumption, and waste in a cafeteria setting. It combines quantitative data (such as food quantity and waste weight) with contextual variables (like weather and customer feedback) to support predictive modelling.

Total Records: Each row represents a specific meal entry for a given day.

- **FEATURES DESCRIPTION**

1. Meal Choice: Indicates the type of meal served — Vegetarian, Vegan, or Non-Vegetarian.
2. Food Item: Specifies the specific dish (e.g., Biryani, Quinoa Salad, Veg Sandwich).
3. Meal Time: States whether the meal was served during Lunch or Dinner.
4. Meals Served: The number of meal portions actually served to customers.
5. Waste (kg): The actual weight of food wasted, recorded in kilograms (target variable).
6. Inventory Used (kg): The amount of raw materials or ingredients used to prepare the meal.
7. Date: The calendar date when the meal was prepared and served.
8. Prediction (Waste (kg)): The predicted food waste value generated by a model (used for validation/comparison).
9. Waste Type: Categorizes the nature of the waste — such as Leftovers or Spoiled food.
10. Reason for Waste: Provides the primary cause of waste (e.g., Overproduction, Low Demand, Stock Mismanagement).
11. Customer Feedback: Captures qualitative feedback from customers about the meal (e.g., Very filling, Great flavor).
12. Weather: Describes the weather conditions on the day the meal was served (e.g., Sunny, Light Rain, Cloudy).

- **KEY VARIABLES FOR PREDICTION**

- Input Features: Meal Choice, Food Item, Meal Time, Inventory Used, Weather, Customer Feedback.
- Target Variable: Waste (kg) – This is the value the model aims to predict.

Meal Choice	Food Item	Meal Time	Meals Served	Waste (kg)	Inventory Used (kg)	Date	prediction(Waste (kg))	Waste Type	Reason for Waste	Customer Feedback	Weather
Vegetarian	Veg Sandwich	Dinner	152.0	9.0	62.0	2025-04-01 00:00:00	9.2	Leftovers	Low demand	Very filling	Light Rain
Vegan	Quinoa Salad	Dinner	117.0	2.0	79.0	2025-04-02 00:00:00	2.3	Spoiled	Low demand	Very filling	Partly Cloudy
Non-Vegetarian	Biryani	Lunch	81.0	5.0	72.0	2025-04-04 00:00:00	5.0	Spoiled	Overproduction	Great flavor	Sunny
Vegan	Quinoa Salad	Lunch	150.0	10.0	72.0	2025-04-04 00:00:00	10.1	Leftovers	Stock mismanagement	Great but heavy	Sunny
Vegan	Vegan Sandwich	Lunch	103.0	9.0	68.0	2025-04-07 00:00:00	8.8	Leftovers	Overproduction	Very filling	Partly Cloudy
Vegan	Tofu Stir-fry	Lunch	92.0	9.0	31.0	2025-04-09 00:00:00	7.7	Leftovers	Overproduction	Great flavor	Light Rain
Vegan	Vegan Sandwich	Breakfast	142.0	10.0	72.0	2025-04-10 00:00:00	10.0	Leftovers	Overproduction	Good but too much rice	Cloudy
Vegetarian	Vegetable Stew	Dinner	126.0	9.0	64.0	2025-04-13 00:00:00	8.9	Spoiled	Low demand	Meat was too fatty	Clear
Non-Vegetarian	Grilled Fish	Dinner	110.0	9.0	72.0	2025-04-14 00:00:00	8.7	Plate Waste	Overproduction	Tasty but too spicy	Partly Cloudy
Non-Vegetarian	Biryani	Lunch	156.0	1.0	56.0	2025-04-20 00:00:00	1.0	Spoiled	Stock mismanagement	Meat was too fatty	Clear
Vegan	Vegan Salad	Breakfast	134.0	9.0	37.0	2025-04-21 00:00:00	8.9	Leftovers	Stock mismanagement	Liked the salad	Light Rain
Non-Vegetarian	Chicken Sandwich	Lunch	146.0	6.0	33.0	2025-04-26 00:00:00	6.2	Spoiled	Low demand	Very filling	Light Rain
Vegan	Vegan Sandwich	Dinner	141.0	2.0	80.0	2025-04-28 00:00:00	2.0	Plate Waste	Stock mismanagement	Not enough flavor	Clear
Non-Vegetarian	Chicken Curry	Dinner	85.0	2.0	76.0	2025-05-01 00:00:00	2.0	Plate Waste	Overproduction	Meat was too fatty	Light Rain
Non-Vegetarian	Biryani	Breakfast	155.0	3.0	65.0	2025-05-02 00:00:00	3.0	Spoiled	Low demand	Very filling	Sunny
Vegetarian	Paneer Curry	Lunch	86.0	8.0	67.0	2025-05-05 00:00:00	8.4	Spoiled	Overproduction	Great but heavy	Light Rain
Non-Vegetarian	Biryani	Lunch	123.0	2.0	54.0	2025-05-05 00:00:00	2.2	Plate Waste	Stock mismanagement	Meat was too fatty	Light Rain
Vegetarian	Veg Salad	Lunch	147.0	2.0	39.0	2025-05-06 00:00:00	2.1	Leftovers	Overproduction	Too dry	Clear
Non-Vegetarian	Biryani	Dinner	71.0	6.0	74.0	2025-05-08 00:00:00	5.8	Spoiled	Low demand	Great but heavy	Sunny
Vegetarian	Vegetable Stew	Lunch	103.0	7.0	64.0	2025-05-10 00:00:00	6.6	Spoiled	Overproduction	Good but too much rice	Light Rain
Non-Vegetarian	Biryani	Dinner	71.0	5.0	58.0	2025-05-10 00:00:00	5.0	Plate Waste	Low demand	Great but heavy	Light Rain
Vegan	Vegan Sandwich	Breakfast	155.0	4.0	47.0	2025-05-11 00:00:00	4.0	Leftovers	Low demand	Meat was too fatty	Light Rain
Non-Vegetarian	Chicken Salad	Dinner	87.0	4.0	60.0	2025-05-13 00:00:00	3.9	Plate Waste	Overproduction	Good but too much rice	Cloudy
Non-Vegetarian	Chicken Sandwich	Dinner	95.0	5.0	48.0	2025-05-14 00:00:00	5.1	Plate Waste	Low demand	Meat was too fatty	Clear
Vegan	Vegan Salad	Breakfast	105.0	1.0	55.0	2025-05-14 00:00:00	1.0	Spoiled	Low demand	Too dry	Clear
Vegetarian	Veg Salad	Lunch	125.0	8.0	79.0	2025-05-16 00:00:00	7.9	Leftovers	Low demand	Very filling	Partly Cloudy
Vegetarian	Vegetable Stew	Lunch	71.0	7.0	57.0	2025-05-23 00:00:00	7.1	Spoiled	Stock mismanagement	Not enough flavor	Partly Cloudy
Vegetarian	Daal	Lunch	120.0	0.0	70.0	2025-05-27 00:00:00	0.0	Plate Waste	Stock mismanagement	Too dry	Cloudy

figure 3.1 Dataset Used

CHAPTER 4 PROJECT DESCRIPTION

The Cafeteria Demand Waste Tracker project is a data-driven initiative aimed at reducing food waste in institutional cafeterias by predicting daily waste levels and uncovering the factors contributing to it. It combines machine learning techniques (via RapidMiner) with dynamic data visualization tools (via Power BI) to help cafeteria managers make informed decisions that optimize meal planning, inventory usage, and overall efficiency.

The project does not stop at prediction—it translates those insights into actionable dashboards and visual reports that help decision-makers track performance, identify waste patterns, and plan ahead with greater accuracy.

- **4.1. PROPOSED DESIGN**

The proposed system follows a modular, data-centric design involving three key components:

- Data Layer: Collects historical data related to meals, waste, weather, inventory, and feedback. This structured data is stored in Excel format and acts as the foundation for modeling.
- Predictive Layer (RapidMiner): Implements machine learning models that use features like meal type, inventory used, food item, and external conditions (e.g., weather) to predict daily food waste (in kilograms).
- Visualization Layer (Power BI): Presents predictive results and key insights through visual dashboards that help cafeteria staff monitor waste trends, compare predicted vs actual waste, and optimize future planning.

The system is designed to be scalable, allowing for new data inputs or feedback loops over time, and interpretable, providing actionable intelligence to non-technical users.

• 4.2 DATA PREPROCESSING

Effective data preprocessing was a critical step in ensuring the model's accuracy and reliability. Key steps included:

- Data Cleaning: Removed missing or irrelevant records, especially in columns like customer feedback and waste reason.
- Feature Encoding: Converted categorical variables (like meal type, food item, weather) into numerical formats using label encoding for compatibility with ML algorithms.
- Normalization: Scaled numerical features such as Inventory Used (kg) and Meals Served to ensure uniform data ranges, reducing model bias.
- Target Variable Definition: Set Waste (kg) as the prediction target, with the goal of forecasting this value using the other input variables.
- Splitting: Divided the data into training and testing sets to validate model performance on unseen data.

The cleaned and transformed data was then used to build a regression model capable of learning patterns and dependencies between input features and food waste levels.

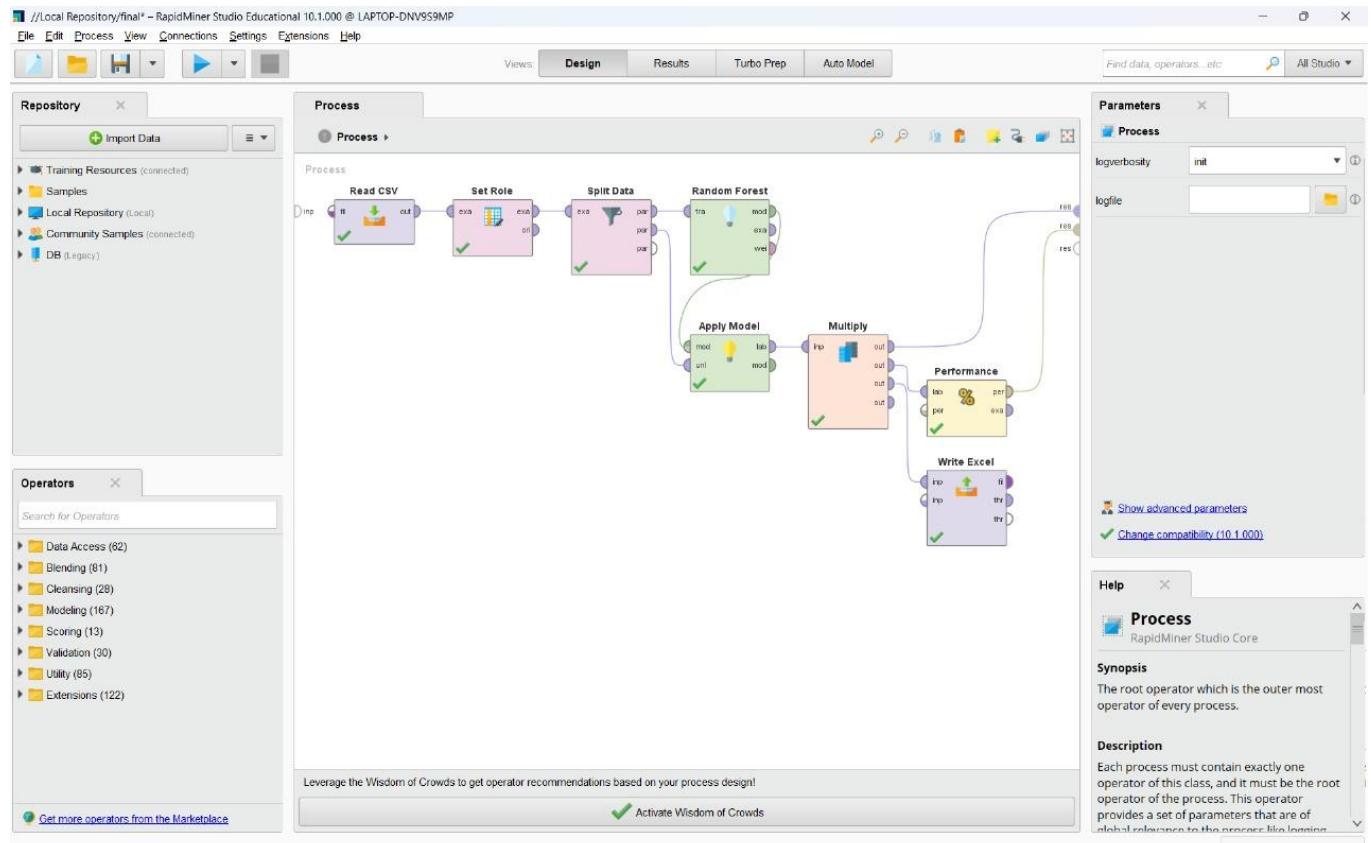


figure 4.2 Rapid miner process

- **4.3 VISUALIZATIONS**

To communicate insights effectively, a series of interactive dashboards were built using Power BI. These dashboards are designed for both operational and strategic use. The dashboard presents multiple visualisations aimed at analysing various aspects of food service operations, including waste, feedback, weather, and inventory metrics. Below is a brief description of each:

1. Sum of Waste (kg) by Feedback Sentiment: A bar chart displaying the total amount of waste generated, categorized by customer feedback sentiment (Negative, Neutral, Positive).
2. Sum of Waste (kg) by Weather: An area chart illustrating the total waste produced under different weather conditions such as Light Rain, Clear, Sunny, Cloudy, and Partly Cloudy.
3. Inventory and Service Metrics Dashboard: A summary section with key performance indicators showing-
 - Total inventory used (kg)
 - Total meals served
 - Total waste (kg)
 - Predicted waste (kg)
 - Average waste per meal
4. Filter Panel: Interactive filters for dynamic analysis including:
 - Meal choice (Non-Vegetarian, Vegan, Vegetarian)
 - Date selection
 - Weather conditions
 - Customer feedback options
5. Weather Overview: A visual grid representing selected weather conditions contributing to the dataset (Cloudy, Partly Cloudy, Light Rain, Sunny).

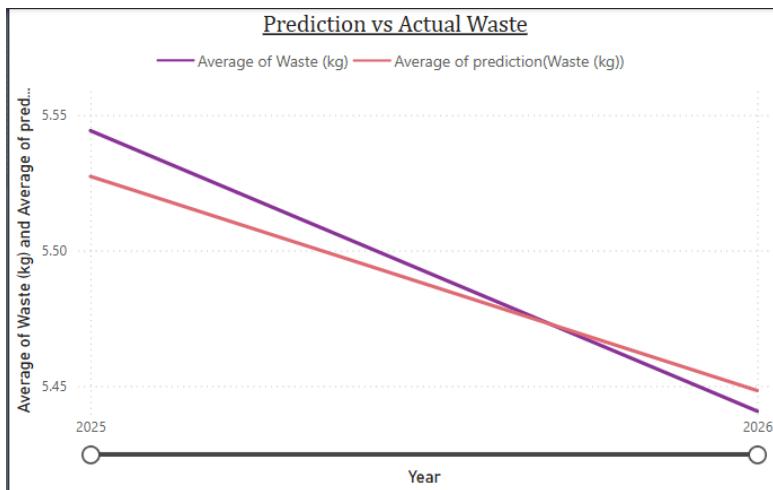


Figure 4.3(a) Prediction vs Actual Waste

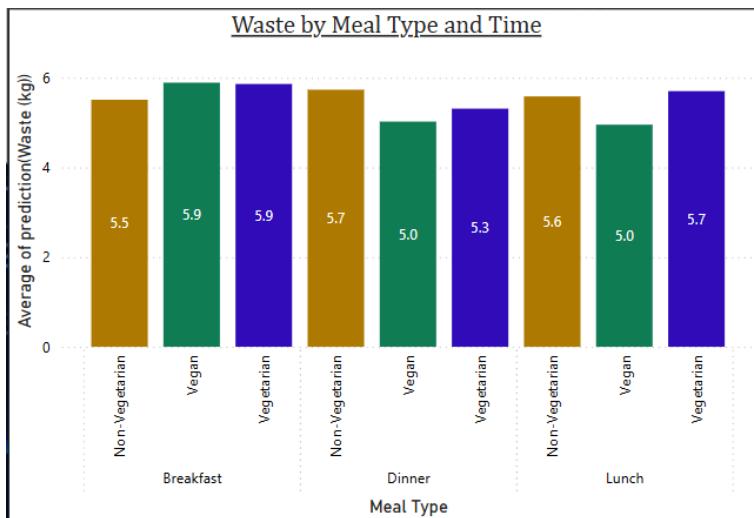


Figure 4.3 (b) Waste by Meal Type and Time

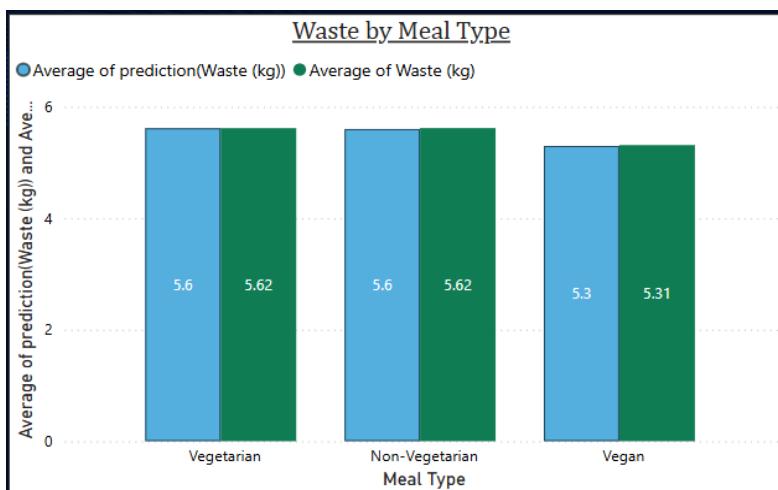


Figure 4.3(c) Waste by Meal Type



Figure 4.3(d) Waste by Food Item

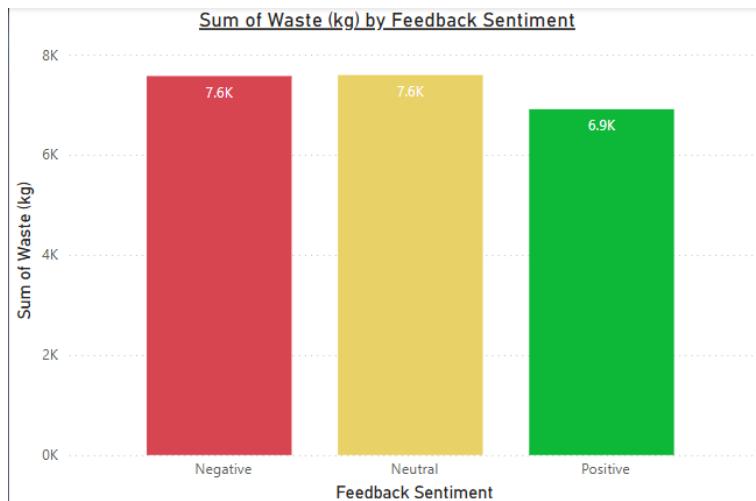


Figure 4.3(e) Waste by Feedback Sentiment

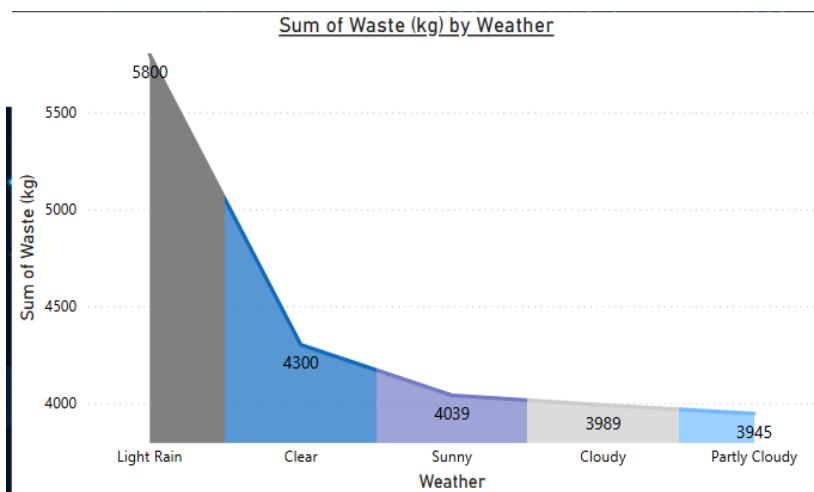


Figure 4.3(f) Waste by Weather

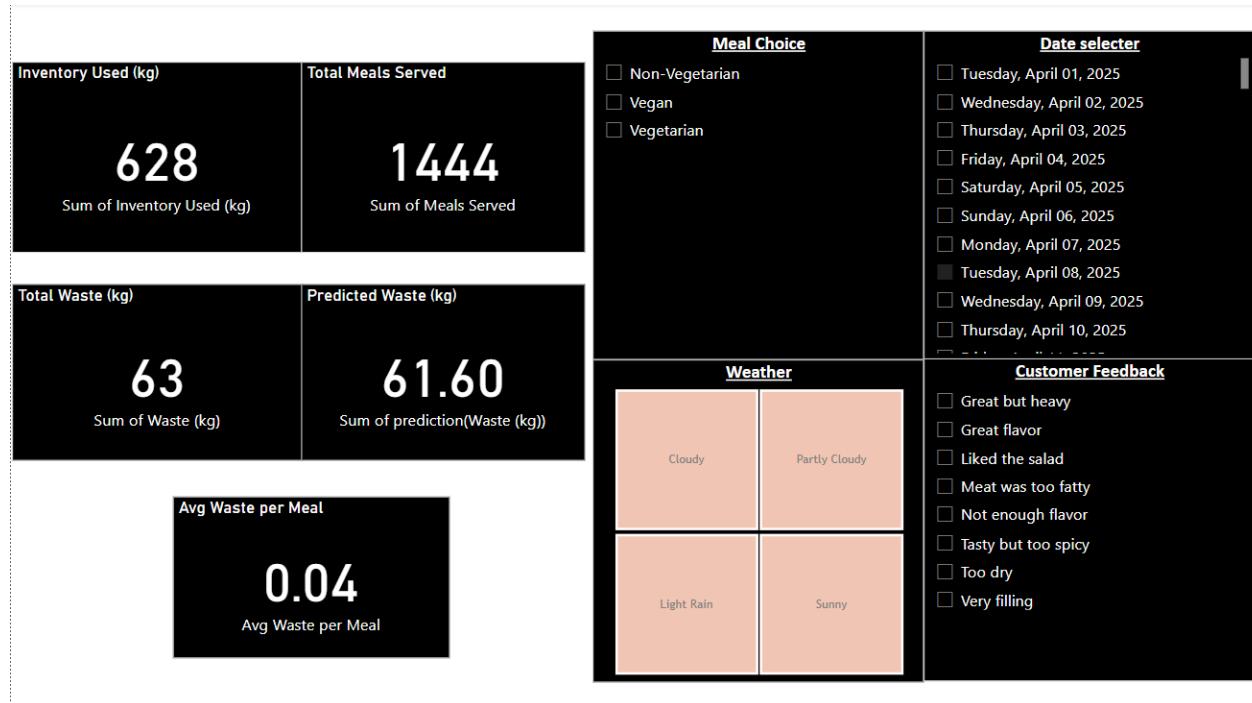


Figure 4.3(g) Summary using Filters and KPIs

- **4.4 INSIGHTS**

From the above graphs we get the below insights.

- *figure 4.2 implies*
 - Both actual and predicted food waste show a declining trend from 2025 to 2026, with predictions closely tracking actual data. This suggests a reliable forecasting model for food waste.
- *figure 4.3 implies*
 - Breakfast: Vegetarian and Vegan options have the highest waste (5.9 kg), followed by Non-Vegetarian (5.5 kg).
 - Dinner: Vegetarian (5.3 kg) and Non-Vegetarian (5.7 kg) meals produce more waste than Vegan (5.0 kg).
 - Lunch: Vegetarian (5.7 kg) and Non-Vegetarian (5.6 kg) again show more waste compared to Vegan (5.0 kg).
 - Vegetarian meals tend to generate the highest average waste across all meal times, while Vegan meals consistently show the lowest waste, especially during dinner and lunch.
- *figure 4.4 implies*
 - Vegetarian: Predicted 5.6 kg vs. Actual 5.62 kg
 - Non-Vegetarian: Predicted 5.6 kg vs. Actual 5.62 kg
 - Vegan: Predicted 5.3 kg vs. Actual 5.31 kg
 - Predictions are highly accurate. Vegan meals still show the lowest waste overall, reinforcing earlier findings.
- *figure 4.5 implies*
 - Biryani and Quinoa Salad are the largest contributors to food waste. Targeting these for portion control or demand forecasting could significantly reduce overall waste.
 - Paneer Curry, Pasta, Vegetable Stew, Tofu Stir-fry, Grilled Fish, are lower waste items.
 - Focused waste-reduction efforts should prioritize high-waste items like Biryani, Quinoa Salad, and Veg Sandwiches for better sustainability impact.

- *figure 4.6 implies*
 - Higher waste levels are associated with negative and neutral feedback.
 - Positive feedback correlates with lower food waste, suggesting better meal satisfaction reduces waste.
 - Targeting improvements that drive more positive sentiment (e.g., quality, service, taste) could lower overall waste.
- *figure 4.7 implies*
 - Waste peaks during light rain, possibly due to lower turnout or canceled orders.
 - Consistently lower waste is seen during stable weather (sunny/partly cloudy).
 - This data could inform inventory planning during rainy conditions to minimize over-preparation.
- *figure 4.8 allows users to*
 - Track inventory-to-waste ratios.
 - See prediction accuracy.
 - Analyze by meal type, weather, date, and customer feedback.
 - Such tools are valuable for operational optimization, reducing waste, and improving customer satisfaction with data-driven decisions.

CHAPTER 5 CONCLUSION

The “Cafeteria Demand & Waste Tracker” project successfully addresses the growing challenge of minimizing food waste while meeting daily cafeteria demand. By integrating the analytical capabilities of RapidMiner with the visualization power of Power BI, the project provides both predictive insight and operational clarity.

Using historical data on meal types, food items, customer turnout, weather, and feedback, machine learning models were developed in RapidMiner to predict food waste more accurately. These models helped uncover patterns such as the impact of low attendance on specific weekdays or the tendency of certain items to consistently produce more waste. Predictive models like decision trees and regression helped forecast expected waste for upcoming meals, empowering kitchen staff to prepare meals in more appropriate quantities.

Parallelly, Power BI dashboards were created to make these insights accessible and actionable. Interactive visualizations showcased key performance indicators such as total waste per day, waste per item, trends over weeks, and the relationship between external factors (like weather) and wastage. The dashboard also allowed for slicing and filtering by meal type, day, and item, making it a practical tool for cafeteria managers to track performance and make quick decisions.

This unified approach provides a comprehensive solution that not only helps in reducing food waste and improving cost-efficiency but also supports sustainability goals. The system allows for better planning, reduces unnecessary inventory usage, and enhances the overall responsiveness of cafeteria operations. By using data to drive decisions, the project sets a strong foundation for smarter, waste-conscious food service management and opens up opportunities for future scalability and automation.

CHAPTER 6 REFERENCES

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