



FOODWASTE AI: PERSONALIZED HOUSEHOLD FOOD WASTE PREDICTION AND SMART RECOMMENDATION SYSTEM

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ABSTRACT :

Household food waste is commonly caused by excessive purchasing, improper inventory management, and failure to consume food before expiry, resulting in food and financial loss. The present study introduces FoodWaste AI, an integrated web-based system that is designed to assist in home food-waste management through food inventory and expiry tracking, waste prediction, recipe recommendation, and event-based grocery planning. The system enables the identification of food items that have the potential to become waste and recommends suitable options for better food utilization. It can also help in festival and event planning by estimating the required grocery items based on user needs and available inventory. The system is implemented using React.js, Node.js and Express.js, MongoDB Atlas, Python-based machine learning, and the Spoonacular API.

Keywords: Food Waste Management, Machine Learning, Random Forest, Food Inventory, Expiry Monitoring, Waste Prediction, Recipe Recommendation, Household Food Management, Festival Planning

1. INTRODUCTION

Household food waste is caused by over-purchasing, poor inventory management, and failure to consume food before expiry, leading to food and financial loss [1], [2], [10], [12], [13], [14], [15]. FoodWaste AI is a web-based system developed to help users manage household food and reduce avoidable waste.

The system provides food inventory management, expiry monitoring, and Random Forest-based waste prediction to identify food items that may become waste [1], [2], [7], [8], [9]. It also provides recipe recommendations through the Spoonacular API to help users utilize available food [4], [6].

Additionally, the system includes festival/event planning and analytics, helping users estimate grocery requirements and understand their food-waste and financial impact. Overall, FoodWaste AI integrates these features into a single platform to support better household food-management decisions [3], [5], [7].

2. LITERATURE SURVEY

2.1 Yang, Zhao and Lu (2024)

Yang, Zhao, and Lu proposed “Leveraging Machine Learning for Food Waste Reduction: An Analysis of Predictive Models.” The study investigated machine learning techniques for predicting food waste using household consumption, retail demand, and food-service data. Random Forest was used to identify important factors influencing food waste. However, the study mainly focused on prediction and did not integrate inventory management, recipe recommendation, event planning, or financial analysis. [1]

2.2 M Anantha Lakshmi et al. (2025)

Lakshmi et al. proposed “Food Waste Management and Prediction Using Machine Learning: A Comprehensive Analysis.” The study used Random Forest to predict future food waste using consumption trends and inventory data. The results indicated that machine learning can support improved food management. However, the work does not provide integrated recipe recommendations, smart notifications, or event-based grocery planning. [2]

2.3 Cappelletti et al. (2022)

Cappelletti et al. presented “Smart Strategies for Household Food Waste Management,” integrating smart refrigerator technology, a web application,

and food-management services. The system focused on inventory monitoring, expiry tracking, and meal planning. However, it did not include machine-learning-based waste prediction, personalized recipe recommendations, or financial analysis. [3]

2.4 Priscilla et al. (2026)

Priscilla et al. developed an AI-Based Food Freshness Detection and Recipe Recommendation System using a CNN to classify food as fresh, medium, or spoiled from images. Recipes were recommended according to the predicted freshness level. However, the system does not address household inventory management, food-waste prediction, or event planning. [4]

2.5 Wafi and Tumiran (2024)

Wafi and Tumiran reviewed the use of Artificial Intelligence for food-waste reduction across the food supply chain. Their study discussed smart inventory management, recipe recommendation, automated waste tracking, predictive analytics, and consumer behaviour analysis. The study highlights the potential of AI but does not present a complete personalized household application. [5]

2.6 Morol et al. (2022)

Morol et al. proposed “Food Recipe Recommendation Based on Ingredients Detection Using Deep Learning.” The system used a CNN to detect food ingredients from images and generate suitable recipe recommendations. Although effective for recipe recommendation, the study does not integrate food-waste prediction, inventory management, or financial analysis. [6]

2.7 Kumar et al. (2026)

Kumar et al. proposed “Food Waste Prediction using Random Forest and Redistribution System.” The system used Random Forest to predict food waste based on food type, quantity, storage conditions, event category, and pricing information. It also supported food redistribution between restaurants, donors, and NGOs. However, its focus is mainly on restaurants and redistribution rather than personalized household food management, recipe recommendations, and festival-based grocery planning. [7]

2.8 Rokhva and Teimourpour (2025)

Rokhva and Teimourpour proposed “Artificial Intelligence in the Food Industry: Food Waste Estimation Based on Computer Vision.” The study used Computer Vision and U-Net-based models to estimate food waste from images. However, it mainly focuses on institutional dining and does not address household inventory management or recipe recommendation. [8]

2.9 Barka-Papadimitriou et al. (2026)

Barka-Papadimitriou et al. proposed a Machine Learning approach for household food-waste management using XGBoost and K-Means. The study focused on analysing household food-waste behaviour. However, it does not provide real-time food-waste prediction, inventory tracking, or recipe recommendations. [9]

2.10 Aitsidou et al. (2026)

Aitsidou et al. studied household food-waste behaviour using data from urban and rural households in Greece. Two-Step Cluster Analysis was used to classify consumers based on their food-waste habits. However, the study does not include Machine Learning-based prediction, inventory management, or recipe recommendation. [10]

2.11 Shao et al. (2026)

Shao et al. studied the impact of food-delivery coupons on household food waste using a Structural Discrete Choice Model. The study focused on purchasing behaviour and unnecessary food purchases. However, it does not provide AI-based food-waste prediction, inventory management, or recipe recommendation. [11]

2.12 Soloha et al. (2026)

Soloha et al. investigated the relationship between household food-management practices and food waste. The study examined meal planning, purchasing, storage, and preparation practices. However, it does not include Machine Learning-based prediction, overbuy detection, or recipe recommendation. [12]

2.13 Salem and Wagner (2025)

Salem and Wagner studied the relationship between overbuying, consumer attitudes, time pressure, and household food waste. The study analysed data from 362 households to understand factors influencing food waste. However, it does not include AI-based prediction, inventory management, or recipe recommendation. [13]

2.14 Abu Hatab et al. (2022)

Abu Hatab et al. examined factors influencing household food-waste behaviour using data from 698 urban households in Addis Ababa, Ethiopia. Structural Equation Modelling and a Binary Logistic Model were used for behavioural analysis. However, the study does not include Machine Learning-based prediction, inventory management, or recipe recommendation. [14]

2.15 Nwafor et al. (2026)

Nwafor et al. examined the effect of household food waste on dietary diversity in Nigeria using data from 1,953 households. The study analysed food-waste levels and their relationship with household dietary diversity. However, it does not include Machine Learning-based food-waste prediction, inventory management, or recipe recommendation. [15]

Table 1. Gap Analysis of Existing Studies

Authors & Year	Focus	Methods Used	Limitation
Yang, Zhao & Lu (2024)	Food waste prediction and reduction	Machine Learning and Random Forest	No integrated inventory management, recipe recommendation, or event planning
M Anantha Lakshmi et al. (2025)	Food waste management and prediction	Random Forest and Machine Learning	No recipe recommendation, smart notifications, or event-based grocery planning
Cappelletti et al. (2022)	Household food waste management	Smart refrigerator, Web Application and Smart Technologies	No ML-based waste prediction, personalized recipes, or financial analysis
Priscilla et al. (2026)	Food freshness detection and recipe recommendation	CNN and Artificial Intelligence	No inventory management, food-waste prediction, or event planning
Wafi & Tumiran (2024)	AI-based food waste reduction	Artificial Intelligence and Predictive Analytics	Review-based study; no complete personalized household application
Morol et al. (2022)	Ingredient detection and recipe recommendation	CNN and Deep Learning	No food-waste prediction, inventory management, or financial analysis
Kumar et al. (2026)	Food waste prediction and redistribution	Random Forest and Artificial Intelligence	Mainly focused on restaurants and NGOs; no personalized household management or recipe recommendation
Rokhva & Teimourpour (2025)	Food waste estimation using Computer Vision	U-Net and U-Net++	Mainly focused on institutional dining; no household inventory or recipe recommendation
Barka-Papadimitriou et al. (2026)	Household food waste behaviour analysis	XGBoost and K-Means	No real-time prediction, inventory tracking, recipe recommendation, or event planning
Aitsidou et al. (2026)	Household food waste consumer typologies	Two-Step Cluster Analysis	No ML-based prediction, inventory management, or recipe recommendation
Shao et al. (2026)	Food delivery and household food waste	Structural Discrete Choice Model	No AI-based prediction, inventory management, recipe recommendation.
Soloha et al. (2026)	Household food management practices	Structured Questionnaire	No ML-based prediction, overbuy detection, recipe recommendation, or financial analytics
Salem & Wagner (2025)	Overbuying and household food waste behaviour	Household survey analysis	No AI-based prediction, inventory management, recipe recommendation, or financial analytics
Abu Hatab et al. (2022)	Household food waste behaviour	SEM and Binary Logistic Model	Focuses on behavioural analysis; no ML prediction, inventory management, or event planning

Nwafor et al. (2026)	Food waste and dietary diversity	Statistical analysis	No ML prediction, inventory management, or recipe recommendation
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3. METHODOLOGY

FoodWaste AI follows an integrated methodology combining household food data processing, machine learning prediction, inventory management, recipe recommendation, and event planning [1], [2], [3], [5], [9]. The system connects the React.js frontend with the Node.js/Express.js backend, MongoDB Atlas, Python-based ML prediction, and Spoonacular API.

3.1 Data Collection and Preprocessing

Household food-waste survey data is collected with information such as food item, category, storage type, quantity, purchase duration, price, shelf life, and consumption outcome. The data is cleaned, inconsistent records are handled, and suitable records are prepared for machine learning. A separate Food Master dataset provides food-related attributes, while the festival dataset supports event-based grocery planning [10], [12], [14], [15].

3.2 Food Waste Prediction

A Random Forest classification model is used to predict whether a food item is likely to be Consumed or Wasted [1], [2], [7]. The model uses food characteristics, quantity, purchase duration, price, storage type, and shelf-life-related attributes. The trained model is accessed through a Python prediction script integrated with the backend [8], [9].

3.3 Inventory and Expiry Management

Users can add, update, use, and record waste for food items through the digital inventory. The system calculates expiry status and identifies food as fresh, expiring soon, expiring today, or expired. This information helps users prioritize food that should be consumed earlier [3], [5], [12].

3.4 Recommendation and Event Planning

The system provides recipe recommendations through the Spoonacular API, prioritizing available and soon-to-expire ingredients [4], [6]. The Event & Festival Planner uses a separate dataset to estimate grocery quantities based on the selected event and guest count and identifies additional items that may need to be purchased [11], [13].

3.5 System Integration

The frontend is developed using React.js, while Node.js and Express.js handle application logic and communication with MongoDB Atlas, the Python ML module, and Spoonacular API. The integrated flow enables FoodWaste AI to provide prediction, inventory management, recommendations, event planning, and analytics through a single platform [3], [5], [7], [9], [15].

4. ARCHITECTURE AND DESIGN

FoodWaste AI follows a modular web-based architecture that integrates the frontend, backend, database, machine learning model, and external recipe service. The architecture is designed to provide secure food management, waste prediction, recommendations, and event-based planning through a single platform.

4.1 System Architecture

The system uses React.js as the frontend, Node.js and Express.js as the backend, and MongoDB Atlas for persistent data storage. The backend acts as the central communication layer between the frontend, database, Python-based Machine Learning model, and Spoonacular API.

System flow:

User → React.js → Node.js/Express.js → MongoDB Atlas / Python ML / Spoonacular API → Response → React.js

The database stores user credentials, food inventory, waste predictions, event information, and notifications. The Python ML module processes food-related inputs and returns the predicted waste risk.

4.2 Module Design

The major modules of FoodWaste AI are:

- **Authentication:** Handles user registration and login.
- **Food Inventory:** Manages food items, quantities, prices, and purchase details.
- **Expiry Monitoring:** Identifies fresh, expiring, and expired food items.

- **Waste Prediction:** Uses Random Forest to predict food-waste risk.
- **Recipe Recommendation:** Uses Spoonacular API to recommend recipes using available ingredients.
- **Event Planner:** Estimates grocery requirements for festivals and special events.
- **Dashboard and Analytics:** Displays inventory, waste, and financial information.

4.3 Data Flow and Interaction

When a user performs an operation, the React.js frontend sends a request to the Express.js backend. The backend validates the request and communicates with MongoDB Atlas or the required external service. For waste prediction, the backend sends food attributes to the Python ML script and receives the prediction result. The processed response is then returned to the frontend and displayed to the user.

5. RESULTS AND DISCUSSION

The proposed FoodWaste AI system was implemented as a web-based household food-management platform using React.js, Node.js and Express.js, MongoDB Atlas, Python-based Machine Learning, and the Spoonacular API. The system provides user authentication, food inventory management, expiry monitoring, food waste prediction, recipe recommendation, festival/event planning, analytics, and notifications. The platform stores user credentials and food-management information in MongoDB Atlas and provides an integrated interface for managing household food resources.

5.1 Results

The developed system provides different modules for managing food items throughout their usage lifecycle. Users can register and log in to the system, maintain their food inventory, monitor expiry information, predict potential food waste, obtain recipe recommendations, and plan grocery requirements for festivals and events. The system also provides dashboard and analytics features to help users understand their consumption, waste, and financial impact.

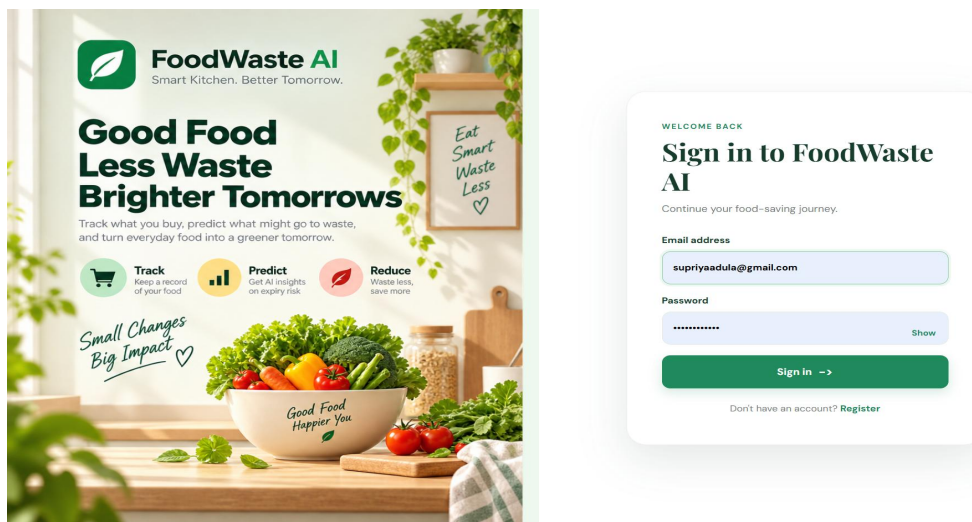


Figure 5.1.1: FoodWaste AI Login Screen

The Login screen provides authenticated access to the FoodWaste AI application. Registered users can enter their credentials to access the application and its available features.

Figure 5.1.2: User Registration Screen

The Registration screen allows new users to create an account by entering the required personal and login details. The registered credentials are securely stored in MongoDB Atlas for authentication.

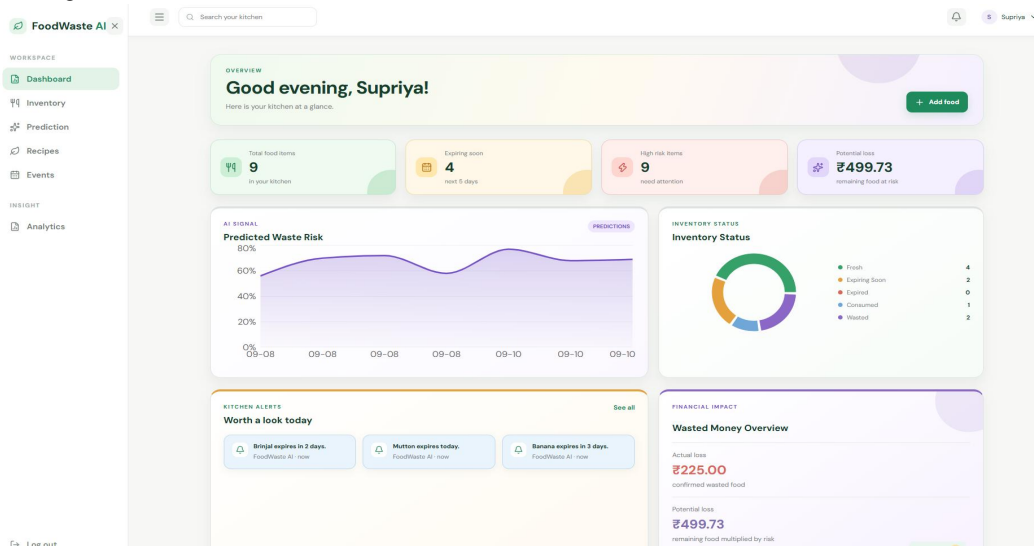


Figure 5.1.3: FoodWaste AI Dashboard

The Dashboard provides an overview of the user's food-management activities. It displays important information related to food inventory, expiry status, food waste, and financial impact.

FOOD ITEM	CATEGORY	QUANTITY	REMAINING	EXPIRY	PRICE	STATUS	ACTIONS
Sugar	Condiments	2 kg	2 kg	2027-09-09 365 days left	₹180	Fresh	Use, Warn, Edit, Delete
Butter	Dairy	1 kg	1 kg	2026-10-09 39 days left	₹150	Fresh	Use, Warn, Edit, Delete
Eggs	Meat & Seafood	2 dozen	2 dozen	2026-09-30 29 days left	₹180	Fresh	Use, Warn, Edit, Delete
Chicken	Meat & Seafood	2 kg	0.5 kg	2026-09-10 9 days left	₹780	Expiring today	Use, Warn, Edit, Delete
Onion	Vegetables	5 kg	4 kg	2026-10-08 39 days left	₹150	Fresh	Use, Warn, Edit, Delete
Banana	Fruits	2 dozen	0.99 dozen	2026-09-13 3 days left	₹150	Expiring soon	Use, Warn, Edit, Delete
Mutton	Meat & Seafood	1 kg	0 kg	2026-09-10 0 days left	₹1800	Consumed	Use, Warn, Edit, Delete
Brinjal	Vegetables	2 kg	0 kg	2026-09-12 2 days left	₹150	Wasted	Use, Warn, Edit, Delete
Apple				2026-09-21			Use, Warn, Edit, Delete

Figure 5.1.4: Food Inventory Management Screen

The Food Inventory screen allows users to view and manage their stored food items. It provides information such as food name, quantity, expiry details, storage type, and available management actions.

Figure 5.1.5: Add Food Item Screen

The Add Food Item screen allows users to add new food items by entering details such as quantity, price, purchase information, category, storage type, and shelf-life information.

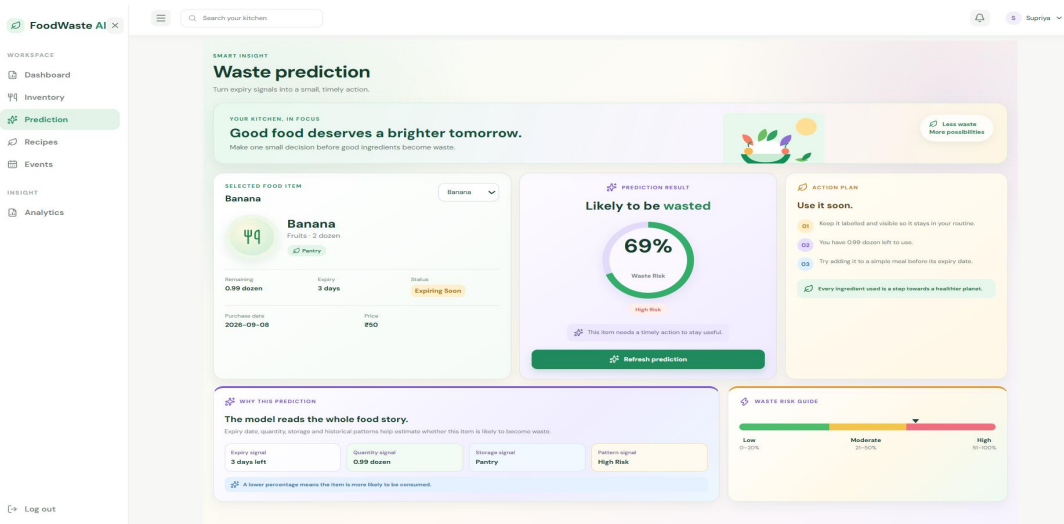


Figure 5.1.6: Food Waste Prediction Screen

The Waste Prediction module uses the Random Forest Machine Learning algorithm to classify food items as Consumed or Wasted. The system provides the predicted waste risk, risk level, prediction result, and suggested action for the selected food item.

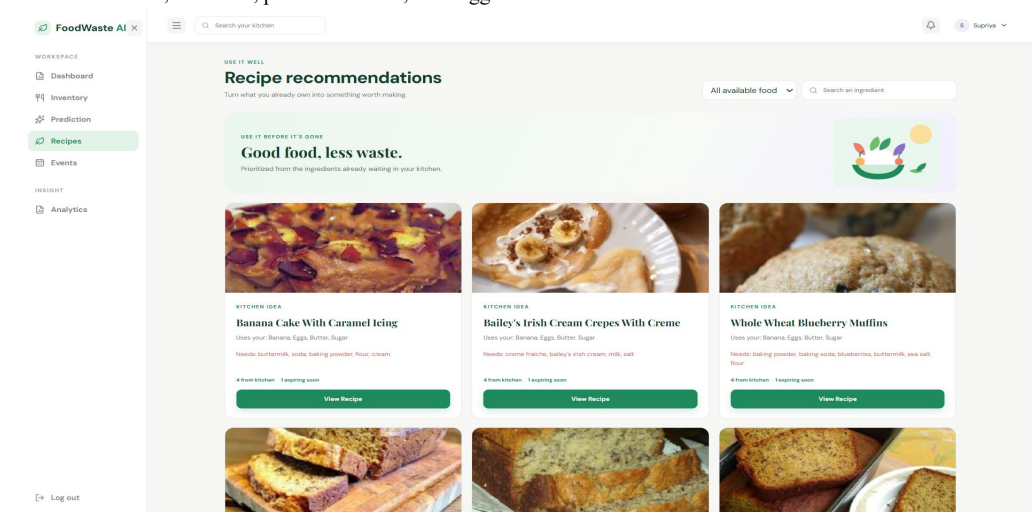


Figure 5.1.7: Recipe Recommendation Screen

The Recipe Recommendation module provides recipes based on ingredients available in the user's inventory. It helps users utilize available food items, particularly those approaching expiry, and thereby reduce potential food waste.

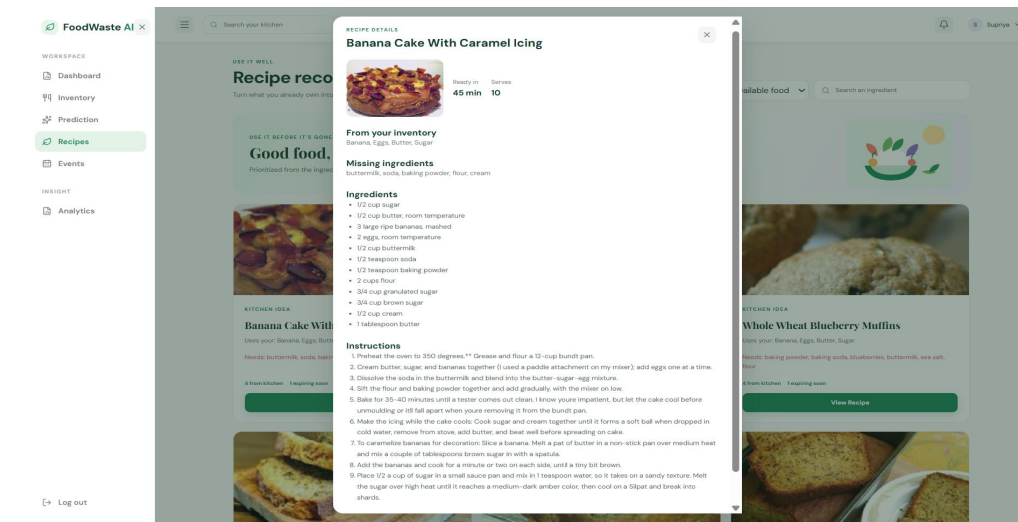


Figure 5.1.8: Recipe Details Screen

The Recipe Details screen provides additional information about a selected recipe, including its ingredients and relevant preparation information.

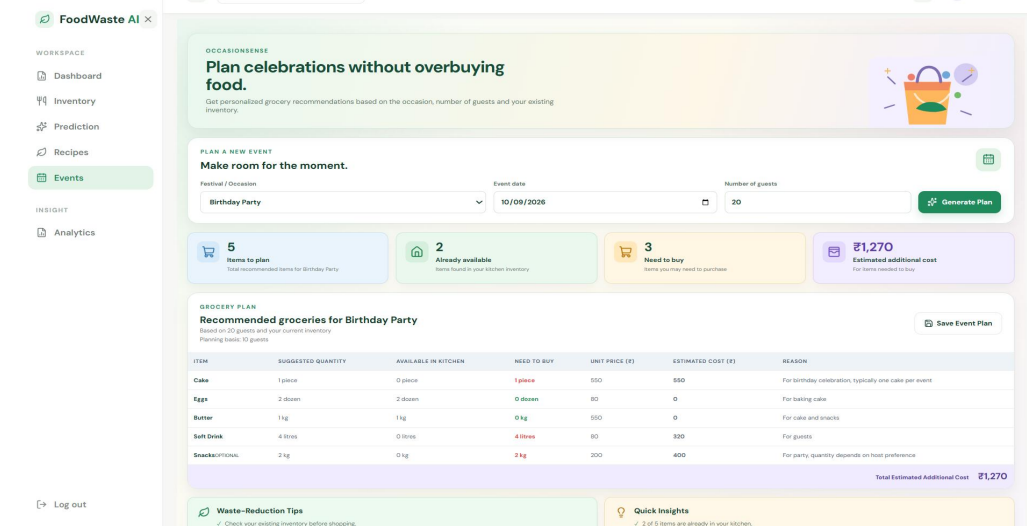


Figure 5.1.9: Festival/Event Planner Screen

The Festival/Event Planner allows users to select an occasion and specify the number of people. The system estimates grocery requirements, compares them with available inventory, and displays required quantities and estimated cost.

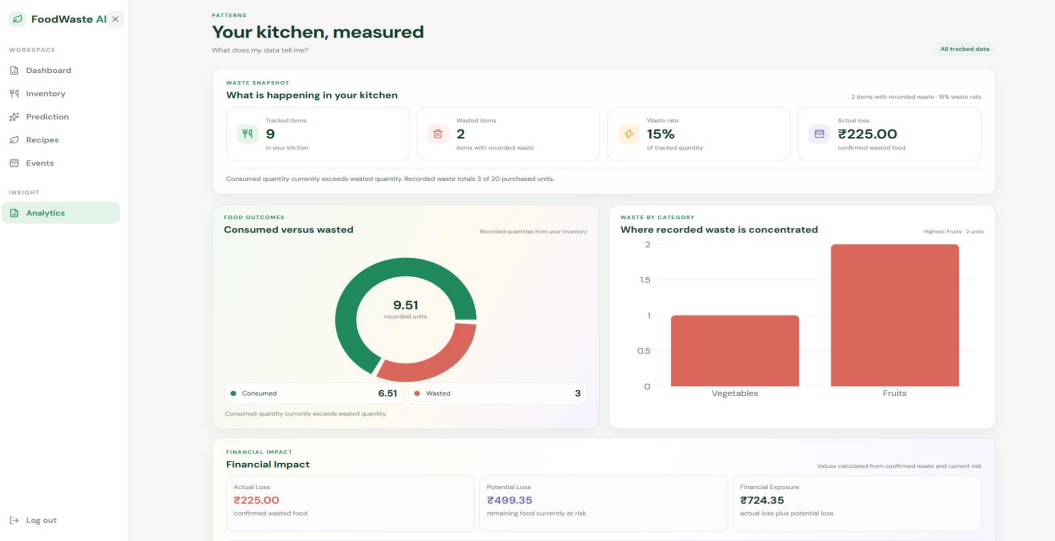


Figure 5.1.10: Food Waste Analytics Screen

The Analytics module provides visual information about food consumption and waste. It displays consumed versus wasted food, waste by category, and

the financial impact of food waste.

5.2 Machine Learning Results

The Random Forest-based food waste prediction model was trained and evaluated using the selected food-related features. On the evaluated test set of 45-record test set, the model achieved 68.89% accuracy, 70.45% precision, 96.88% waste recall, and 81.58% waste F1-score. The model achieved a balanced accuracy of 48.44% using a prediction threshold of 0.50. The results indicate that the model can provide useful predictive information for identifying food items that may be at risk of becoming waste. However, the model performance alone does not establish a direct reduction in actual household food waste.

5.3 Discussion

The results demonstrate that FoodWaste AI integrates food inventory management, expiry monitoring, Machine Learning-based waste prediction, recipe recommendation, event planning, and analytics within a single platform. The combination of waste prediction and recipe recommendation helps users identify potentially wasted food and find suitable ways to utilize available ingredients.

The Random Forest model achieved 68.89% accuracy on the evaluated test set, indicating that it can provide useful predictive information for identifying food items that may be at risk of becoming waste. However, the model performance alone does not establish a direct reduction in actual household food waste. Further improvement can be achieved through larger and more diverse food-waste datasets and additional food-related features.

6. CONCLUSION

FoodWaste AI presents an integrated web-based solution for household food-waste management by combining inventory management, expiry monitoring, food-waste prediction, recipe recommendation, and event planning. The system integrates React.js, Node.js, MongoDB Atlas, Python-based Machine Learning, and the Spoonacular API to support effective food utilization and smarter household decisions. The developed platform provides a practical approach to supporting better food utilization, informed household food-management decisions, and the identification of food items that may be at risk of becoming waste.

7. FUTURE SCOPE

The proposed system can be further improved by using larger and more diverse household datasets to enhance the performance of food-waste prediction. Future versions can incorporate advanced Machine Learning techniques and personalized recommendations based on individual consumption patterns. Computer Vision can also be integrated for automatic food and freshness detection. The Event & Festival Planner can be extended with more occasions and improved grocery estimation. Mobile application support and advanced notification features can further improve the usability and accessibility of the system.

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