Foodwise: AI-Based Food Waste Reduction and Redistribution System Using Predictive Analytics

Ajay Kannaujiya[1] ,Abhishek Mishra[2], Indraraj Singh[3], Amit Patel[4],Aman Mishra[5]

[1234]UG student of the Department of Information Technology , Goel Institute Of Technology and Management Lucknow, Uttar Pradesh, India

[5]Assistant Professor of the Department of Information Technology, Goel Institute Of Technology and Management Lucknow Uttar Pradesh, India

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Abstract - *Food waste is a major global issue that coexists with hunger and food insecurity. A significant portion of food prepared by restaurants, hotels, hostels, and dhabas remains unsold and is eventually discarded. This paper proposes Foodwise, a smart food waste management system that integrates predictive analytics and a redistribution platform to minimize food wastage. The system collects daily data on food preparation and sales from food service providers and employs a Random Forest regression model to predict the optimal preparation quantity for the next day. Surplus food is automatically listed on a web platform, enabling non-governmental organizations (NGOs) and individuals to collect and distribute it to needy populations. The model continuously retrains using new data, improving prediction accuracy over time. The proposed system aims to reduce food waste, optimize operational efficiency, and contribute to social welfare.*

Keywords—Food Waste Management, Machine Learning, Random Forest, Predictive Analytics, Food Redistribution, Smart Systems, Django, Scikit-learn.

1.INTRODUCTION

Food waste has emerged as a critical global challenge, impacting not only environmental sustainability but also economic efficiency and food security. A significant proportion of food prepared in restaurants, hostels, hotels, and community kitchens remains unsold due to demand uncertainty, poor planning, and lack of data-driven decision-making. At the same time, a large section of the population continues to face food insecurity, highlighting a clear mismatch between surplus generation and redistribution mechanisms.

To address this gap, Foodwise proposes an integrated, intelligent platform that combines machine learning with real-time food redistribution. The system is designed to assist food providers in optimizing daily food preparation while simultaneously enabling efficient redistribution of surplus food to needy individuals and organizations.

The core of the system lies in its ability to learn from historical food preparation and consumption patterns. Each day, the system records key parameters such as prepared quantity, sold quantity, and generated waste through structured data models. These records are then used to train predictive models that estimate future demand. The implemented approach leverages a Random Forest regression model, which considers temporal features (day of the week and month) along with recent consumption trends to generate accurate preparation recommendations.

In addition to predictive analytics, the system incorporates a real-time redistribution module. Once the day is closed and surplus food is identified, available quantities are dynamically listed on a public interface. NGOs and individuals can browse available food, submit requests, and schedule pickups through a structured request management workflow. This ensures that surplus food is not only minimized at the source but also effectively utilized.

Furthermore, the system extends beyond regular food providers by including event-based donations, such as wedding surplus food, thereby expanding the redistribution ecosystem. The integration of user-friendly dashboards, data visualization (prepared vs. sold vs. waste trends), and automated notifications enhances usability for stakeholders.

Overall, Foodwise represents a shift from reactive waste handling to proactive waste prevention, combining artificial intelligence, web-based interaction, and social impact into a unified framework.

2.SCOPE

The scope of the Foodwise system encompasses both technological and societal dimensions, focusing on reducing food waste at its source and improving the efficiency of surplus food distribution.

From a technological perspective, the system is designed as a full-stack web application built on a scalable backend framework. It supports multi-user interaction where each food provider maintains independent records and predictive models. The machine learning component operates at an individual item level, meaning that separate predictive models are trained for each food item per user, enabling personalized and context-aware recommendations.

The predictive module considers historical daily records—including prepared, sold, and wasted quantities—along with short-term moving averages to capture recent trends.

In cases where insufficient historical data is available, the system falls back to heuristic-based estimation, ensuring robustness and continuity of operation.

On the operational side, the scope includes:

- Food Preparation Optimization: Assisting restaurants, hostels, and similar establishments using AI-driven predictions.
- Waste Monitoring and Analytics: Providing visual insights into food waste trends over time.
- Surplus Food Redistribution: Enabling real-time listing of leftover food and facilitating structured requests from NGOs and individuals.
- Request Management System: Supporting request creation, acceptance, rejection, and scheduling of food pickups.
- Event-Based Donations: Allowing large-scale food donations from events such as weddings.
- User and Location Management: Maintaining restaurant profiles with location data.

The system is intended for deployment in urban and semi-urban environments where food waste is significant and digital access is available. Future enhancements can incorporate real-time data sources and more advanced predictive techniques.

3. OBJECTIVES

The primary objective of the proposed system is to minimize food waste at its source while ensuring efficient redistribution of surplus food to those in need, by integrating predictive analytics, real-time data tracking, and a structured request management workflow.

A key objective is to enable data-driven decision-making for food providers. By analyzing historical records of prepared, sold, and wasted food, the system generates accurate preparation recommendations. Another important objective is to establish a seamless bridge between food surplus and food demand by automatically identifying leftover food and making it available through a public interface.

The system also aims to enhance transparency and operational efficiency through visualization and monitoring tools. The specific objectives are summarized as follows:

- Reduce food waste using predictive analytics and historical data modeling.
- Optimize daily food preparation for food service providers.
- Facilitate real-time redistribution of surplus food.
- Create an efficient and transparent request and pickup management system.
- Support community-driven food donation initiatives, including event-based donations.

4. LITERATURE REVIEW

Food waste management has been an active area of research, with various approaches proposed to tackle the problem from technological, logistical, and social perspectives.

One major area of research involves demand forecasting using statistical and machine learning techniques. Traditional methods such as time-series analysis and regression models have been widely used to estimate food demand in hospitality environments [1]. However, these approaches often struggle to capture non-linear patterns and dynamic consumption behavior. Recent studies have explored ensemble techniques like Random Forests to improve prediction accuracy [2].

Another significant area is food redistribution systems, which aim to connect surplus food providers with consumers in need. Several platforms have been developed to facilitate donation and redistribution, but many rely heavily on manual input and lack predictive capabilities [3][4]. As a result, they address the consequences of food waste rather than preventing it at the source.

Research has also highlighted the importance of real-time data collection and digital platforms in reducing food waste [5]. However, many existing solutions focus either on analytics or redistribution, rarely combining both into a cohesive framework.

In recent years, hybrid approaches have gained attention where predictive analytics is combined with redistribution mechanisms. Challenges remain in terms of scalability, user adaptability, and integration of multiple stakeholders [6].

The proposed Foodwise system builds upon these existing studies by integrating machine learning-based demand prediction with a real-time redistribution platform. Unlike traditional systems, it uses item-level historical data to train individualized predictive models, enabling more precise recommendations. Additionally, it incorporates a structured request and scheduling mechanism, ensuring that surplus food is efficiently allocated and collected.

5. METHODOLOGY

The Foodwise system follows a data-driven and modular methodology that integrates data collection, machine learning-based prediction, and real-time redistribution into a unified workflow. The methodology is designed to ensure continuous learning, adaptability, and efficient utilization of food resources.

5.1 Data Acquisition

Food providers input daily records including item name, prepared quantity, and sold quantity. The system automatically computes waste as the difference between prepared and sold quantities, ensuring consistency and eliminating manual errors. These records are stored in a structured database and uniquely maintained per user and per day, forming the foundation for predictive modeling.

5.2 Data Preprocessing and Feature Engineering

Historical records are organized chronologically, and additional features are derived to improve prediction accuracy. These include temporal attributes such as day of the week and month, as well as short-term moving averages of prepared, sold, and waste quantities over recent days. This enables the model to capture both seasonal patterns and recent consumption trends.

5.3 Model Training

The engineered features are used to train a Random Forest regression algorithm to predict the quantity of food to be prepared for the next day. The model is trained separately for each food item and each user, ensuring personalization and higher accuracy. In scenarios where insufficient historical data is available, the system adopts a fallback heuristic approach based on recent averages and observed waste.

5.4 Prediction and Recommendation Generation

When a user closes the day, the model predicts the optimal preparation quantity for the next day. These predictions are stored and displayed through an intuitive interface, enabling informed decision-making. The model is continuously retrained with new daily data to improve accuracy over time.

5.5 Waste Identification and Redistribution

Once the day is closed, leftover food items with positive waste quantities are automatically identified as available for donation. The system dynamically calculates available quantities by subtracting previously requested amounts, ensuring accurate and fair allocation. External users such as NGOs can view available food, submit requests specifying quantity and preferred pickup time, and receive updates on request status

6.PROPOSED SYSTEM ARCHITECTURE

The proposed methodology enhances traditional food waste management approaches by combining predictive analytics with real-time redistribution in a scalable web-based system. It is structured into interconnected modules that collectively address both prevention and utilization of food waste.

6.1 Intelligent Prediction Module

This module leverages machine learning to forecast food demand. Unlike conventional systems that rely on static rules, it dynamically adapts to historical patterns and recent trends. Ensemble learning techniques enable the system to handle variability in demand and improve prediction reliability over time.

6.2 Dynamic Waste Tracking Module

This module continuously monitors food preparation and consumption. By automatically calculating waste and maintaining historical records, it provides accurate insights into inefficiencies and supports long-term optimization strategies.

6.3 Real-Time Redistribution Module

This module acts as a bridge between surplus food providers and potential beneficiaries. It ensures that leftover food is immediately visible and accessible, reducing delays and minimizing spoilage. The system accounts for previously allocated quantities, preventing overbooking and ensuring fair distribution.

6.4 Request Management and Scheduling Module

This module introduces structure and accountability into the redistribution process. By allowing users to specify pickup times and enabling providers to schedule requests, it reduces coordination issues and improves operational efficiency. Requests move through states: pending, accepted, scheduled, and rejected.

6.5 Event-Based Donation Module

This module extends functionality to large-scale food surplus scenarios such as weddings and public events. Event organizers enter food donation details including location, quantity, and availability time. These donations are displayed alongside regular surplus food, increasing the volume of recoverable food and broadening the system's impact

7. TECHNOLOGY STACK

The implementation of Foodwise relies on a combination of modern web technologies and machine learning tools. Table I summarizes the technologies used.

Table -1: Technology Stack of the Foodwise System

Component	Technology
Backend Framework	Django (Python)
Language	Python 3.x
ML Library	Scikit-learn
Model Persistence	Joblib
Database	PostgreSQL
Frontend	HTML5, CSS3, JS
Auth System	Django Auth

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8. SYSTEM DESIGN

The system design of Foodwise is represented through an Entity-Relationship (ER) Diagram, a Use Case Diagram, and a Data Flow Diagram (DFD), which collectively capture the data model, actor interactions, and information flow within the system.

8.1. Entity-Relationship Diagram

The ER diagram (Fig. 1) illustrates the core entities of the system—User, FoodItem, DailyRecord, SurplusListing, and Request—along with their relationships. Each User maintains multiple DailyRecords keyed by date and item. Surplus listings are derived from closed daily records and linked to incoming Requests from NGOs.

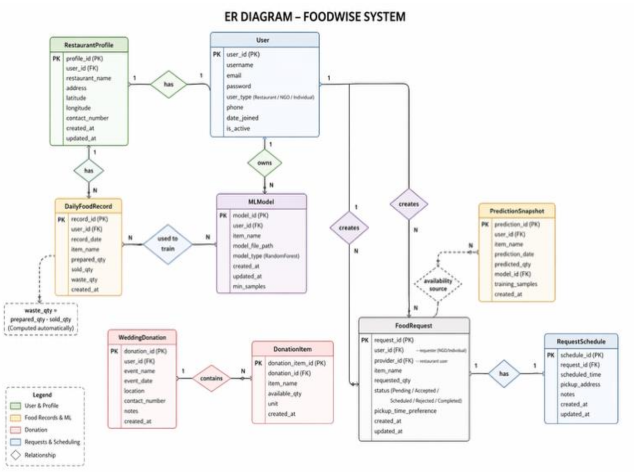

Fig -1: E-R Diagram

8.2 Use Case Diagram

The Use Case diagram (Fig. 2) defines the interactions between the two primary actors—Food Provider and NGO/Recipient—and the system. Key use cases include daily data entry, day closure, prediction retrieval, surplus listing, food request submission, and request scheduling.

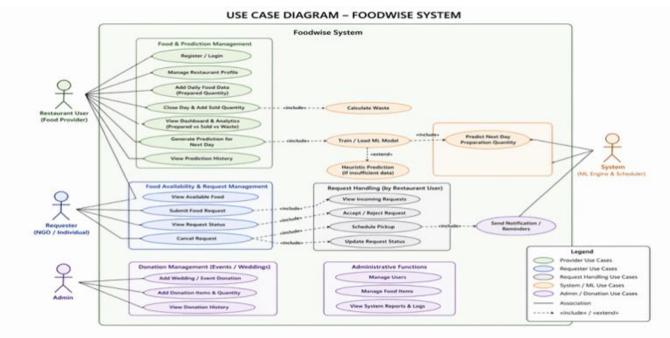

Fig -2: Use Case Diagram

8.3 Data Flow Diagram

The Data Flow Diagram (Fig. 3) models the movement of data through the system. At Level 0, the DFD shows the system as a single process receiving food data from providers and returning predictions and surplus listings. Level 1 decomposes this into sub-processes: data entry, waste calculation, model training, prediction generation, and redistribution.

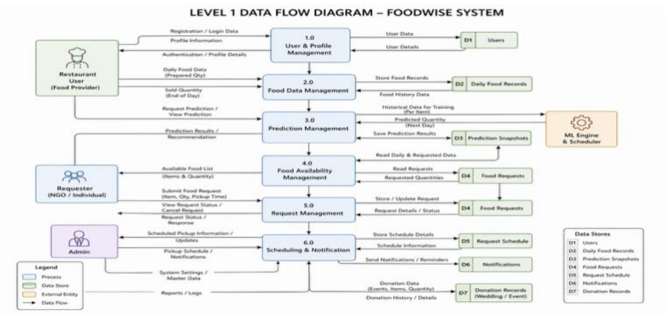

Fig -3: Data Flow Diagram

9. IMPLEMENTATION

9.1 Home Screen

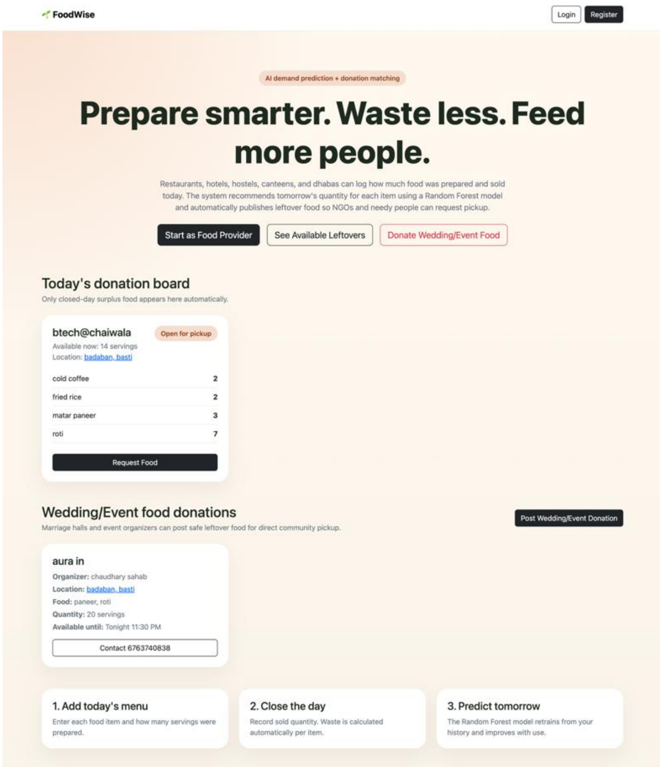

Fig -4: Home Screen

9.2 Restaurent Register Screen

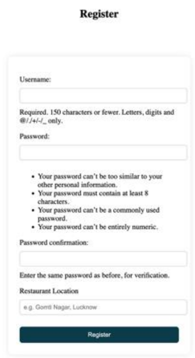

Fig -5: Restaurent Registration Screen

9.3 Restaurent Login Screen

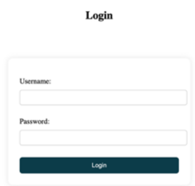

Fig -6: Restaurent Login Screen

9.4 Restaurent Dashboard

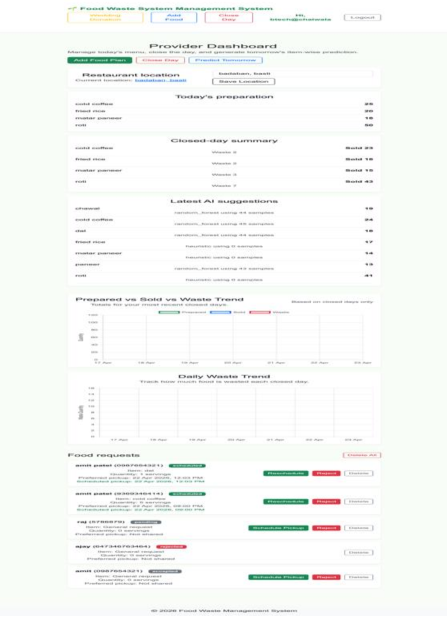

Fig -7: Restaurent Dashboard

9.5 Add Food Plan

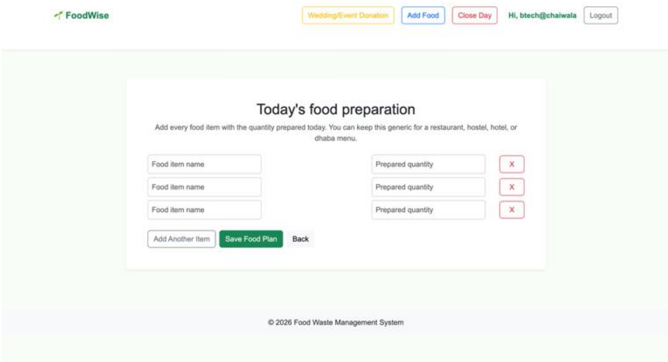

Fig -8: Add Food Plan

9.6 Close Day

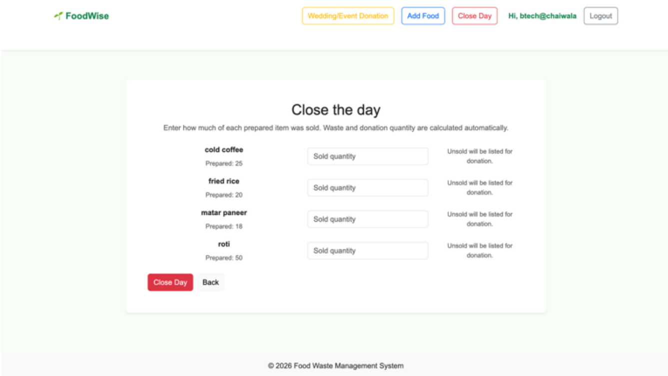

Fig -9: Close Day

9.7 Predict Tomorrow

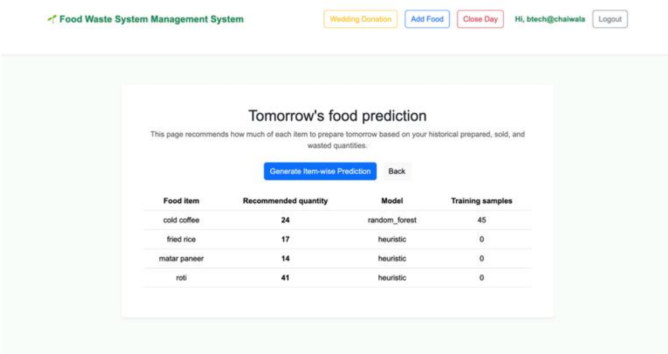

Fig -10: Predict Tomorrow Food

9.8 Food Request

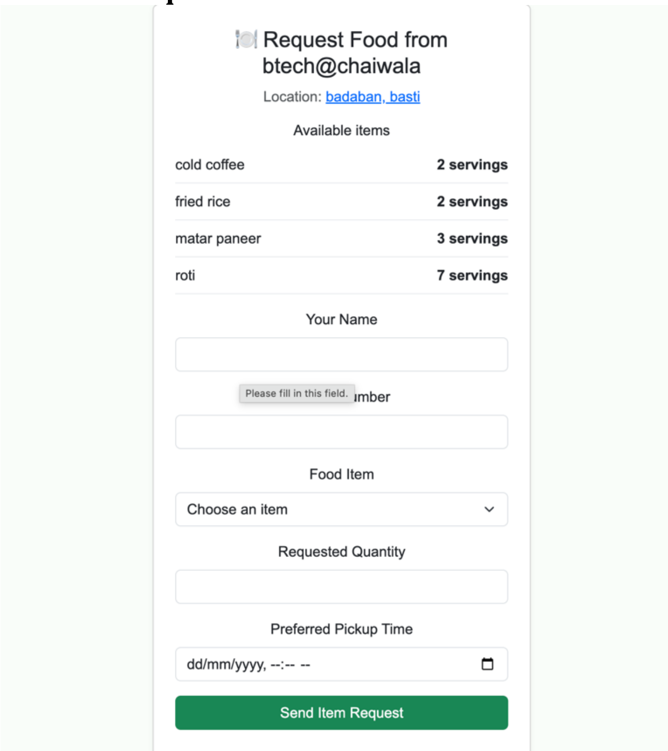

Fig -11: Food Request

9.9 Wedding/Event Donation

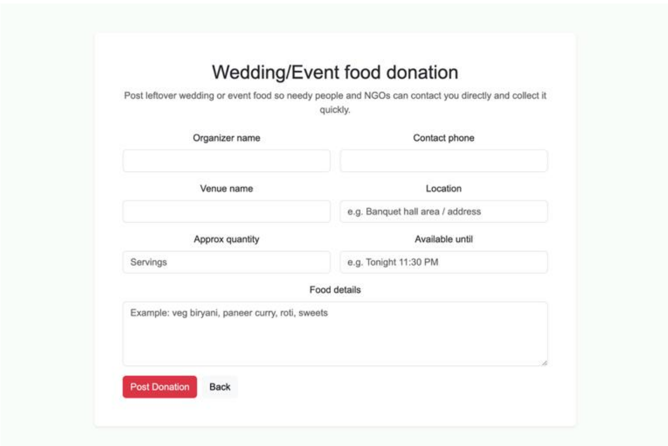

Fig -12: Wedding/Event Donation

10. SYSTEM FLOW

The Foodwise system follows a structured and sequential workflow that integrates food data collection, predictive analytics, and surplus food redistribution into a continuous cycle, as illustrated in Fig. 13.

10.1 User Registration and Profile Setup

Food providers register on the platform and create profiles by providing essential details including location. This information is used for accessibility and coordination during food redistribution.

10.2 Daily Food Data Entry

After login, the food provider enters daily food preparation details—item name and prepared quantity—for each menu item. The system ensures consistency by updating existing records rather than duplicating them.

10.3 Day Closure and Waste Calculation

At the end of the day, the provider inputs the sold quantity for each item. The system then: (1) computes Waste = Prepared − Sold; (2) marks the record as finalized (closed day); and (3) makes historical data available for model training.

10.4 Prediction Generation

After day closure, the system retrieves historical records, constructs feature vectors using recent trends and temporal attributes, and trains or reuses a Random Forest model to generate recommended preparation quantities for the next day. If sufficient data is unavailable, a heuristic fallback is applied.

10.5 Dashboard and Analytics Visualization

The system provides a dashboard displaying prepared vs. sold vs. waste trends, daily waste patterns, and prediction results, enabling users to continuously refine their planning strategy.

10.6 Surplus Food Identification and Redistribution

Once the day is closed, the system identifies leftover items with positive waste quantities, calculates available quantities (subtracting already requested amounts), and prepares a real-time list for redistribution. NGOs view available food, submit requests with quantity and pickup time, which are validated and assigned a "pending" status.

10.7 Request Processing and Scheduling

Food providers manage incoming requests through their dashboard, accepting, rejecting, or scheduling pickups. Once scheduled, the request status is updated and both parties can view the final schedule, ensuring smooth coordination.

10.8 Event-Based Donation Flow

Event organizers enter food donation details (location, quantity, availability time). These donations are displayed alongside regular surplus food, extending the system's capability to handle large-scale food redistribution.

10.9 Continuous Feedback Loop

The system operates in a closed loop: daily data is collected, predictions are generated, waste is reduced, remaining surplus is redistributed, and new data continuously improves future predictions.

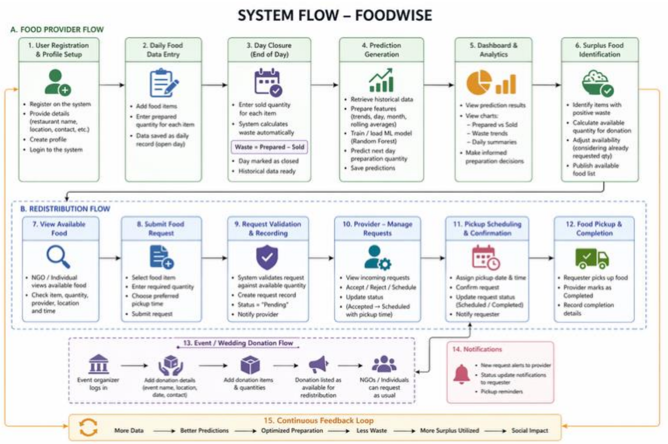

Fig -13: System Flow

11. RESULTS AND DISCUSSION

The implementation of the Foodwise system demonstrates significant improvements in both food waste reduction and efficient redistribution. The system was tested using real-time inputs and simulated historical datasets to evaluate its predictive accuracy and operational effectiveness.

One of the primary outcomes observed is a measurable reduction in excess food preparation. By utilizing historical data and machine learning-based predictions, the system provides recommended preparation quantities that are closely aligned with actual demand. Over time, as more data is accumulated, prediction accuracy improves due to the continuous learning mechanism.

Visualization dashboards show a gradual decrease in waste trends as users begin to rely on prediction outputs rather than manual estimation, indicating the effectiveness of the Random Forest model in minimizing overproduction. The structured request handling mechanism ensures that: (1) requests are validated against available quantities; (2) over-allocation is prevented; and (3) pickup scheduling is streamlined.

The request management workflow shows high efficiency, with requests moving seamlessly through pending, accepted, scheduled, and rejected stages. The inclusion of event-based donation functionality increases the overall volume of food redistributed, particularly in large-scale scenarios such as weddings. From a system performance perspective, the application handles multiple users independently with personalized per-user, per-item predictive models, and model persistence via Joblib ensures efficient prediction generation.

Overall, the results indicate that Foodwise effectively achieves its dual objective of reducing food waste at the source and maximizing the utilization of surplus food through redistribution.

12. CONCLUSIONS

Foodwise presents a practical and scalable solution to the growing problem of food waste by integrating predictive analytics with a real-time redistribution platform. The system moves beyond traditional reactive approaches and introduces a proactive mechanism that minimizes waste during the food preparation stage itself.

By leveraging Random Forest-based prediction models, the system enables food providers to make informed decisions regarding daily preparation quantities, significantly reducing the likelihood of overproduction. Any unavoidable surplus is efficiently redistributed to those in need through a structured and transparent request management system.

The modular design, combined with user-friendly interfaces and automated workflows, makes the system suitable for deployment in real-world environments such as restaurants, hostels, and event venues. Future improvements can include:

Integration of external factors such as weather, festivals, and seasonal trends.

Adoption of advanced deep learning or LSTM time-series models for improved prediction accuracy.

Mobile application support for wider accessibility.

Integration with logistics and delivery services for faster redistribution.In conclusion, Foodwise demonstrates how technology and data-driven approaches can address both environmental and social challenges, providing a sustainable framework that reduces food waste and contributes to food security and community welfare.

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