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Food Waste Prediction using Random Forest and Redistribution System

Vineet Kumar[1], Arun A.[2], Devansh Om Saxena[3], Saksham Uniyal[4]

[1,3,4]Student, [2]Associate Professor, Department of Networking and Communications, School of Computing, Faculty of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur, India.

E-mail: [1]vk0327@srmist.edu.in, [2]aruna2@srmist.edu.in, [3]ds9172@srmist.edu.in, [4]su2807@srmist.edu.in

Abstract

Food wastage is a critical global issue results in significant environmental degradation, economic loss and food insecurity. This paper proposes an AI-enabled food waste prediction and redistribution system will help to reduce food wastage by smartly connecting restaurants and food donors with NGOs nearby. A proposed system integrates a web-based architecture with comprehensive machine learning, geospatial intelligence and real-time communication mechanisms to enable efficient food redistribution. This system predicts wastage of food items with the help of a Random Forest-based machine learning model along with contextual parameters of food type, quantity, event category, storage conditions and pricing details. The backend of this system depends on FastAPI and uses secure role-based authentication using JWT. The frontend is designed on React algorithm and includes specific roles in dashboards for restaurants, NGOs and administrators to access. Automatic email notifications support involvement of stakeholders for geographic connection increases their contribution using map-driven decision-making, distance computation reduces logistical delays and improving efficiency. Overall, the system demonstrates the AI and GIS technology can be efficiently combined to generate a low-cost, scalable and long-term solutions for reducing food waste and improving shared meals.

Keywords: Artificial Intelligence, Random Forest, Food Waste Management, Machine Learning Prediction, Location-Based Services, Food Redistribution System.

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1. Introduction

Food wastage is a major social issue caused by limited production, inaccurate demand of food and transport difficulties make the continuous food hunger. The standard food donation methods are manual and the results are unpredictable such as delayed collections and wastage of food [7-9]. This study addresses two related issues: food waste prediction and redistribution optimization. The excess food prediction is considered as a supervised regression issue using historical and contextual data with a machine learning model used for real-time forecasting. The redistribution combines contributors with local NGOs based on prediction and spatial limits using rule-based filtering, geospatial computations and process automation. This work will promote modularity, interpretability and scalability. The existing systems failed to handle the issues like smart prediction, identification of location and high access authority for active decision-making.

The proposed system combines machine learning, spatial data and web-based design to help restaurants, non-governmental organizations and administrators distribute extra food to the people suffered from hunger. The key contributions include: (i) End-to-end analyzing of machine learning prediction into effective distribution, (ii) efficient accurate NGO-donor matching and (iii) a secure, role-based architecture with automated notifications enable scalable implementation for public and professional food waste management.

2. Literature Survey

Food waste management is a major global challenge due to its environmental, economic and social impacts. Recent research increasingly leverages AI and machine learning (ML) to predict, control and reduce food waste across the supply chain. Existing studies fall into four areas: (i) waste characterization and biochemical processing, (ii) predictive modeling and demand forecasting, (iii) redistribution and logistics optimization and (iv) system-level frameworks aligned with circular economy principles.

Existing research focuses on following works. For example, Dehghan et al. [1] and Kravchenko et al. [2] used ML to estimate waste composition and biochar properties, while Lytras et al. [3], Lai et al. [18], and others applied ML to optimize composting and anaerobic digestion [5,10,13,14,16]. Predictive analytics at earlier stages, such as campus dining [6] or agriculture [4], aim to reduce overproduction but these tools are often isolated and lack integration with real-time redistribution.

Some studies solve prediction with operational systems, integrating ML with IoT and blockchain [11], or analyzing waste classification [12,19]. Research on redistribution and logistics emphasizes social impact, efficiency and human–AI collaboration [20–24], but lack smart prediction, geospatial automation and secure role-based systems. The methods exist [15] but rarely connect to deployable platforms.

Overall, food waste research remains disintegrated. The proposed system addresses this issue by combining ML-based prediction, geospatial accurate location, secure role-based access and real-time coordination between restaurants and NGOs transforming AI results into practical impact on society.

Table 1. Comparative Analysis of Existing Research and Identified Gaps

Study Category	Prediction Model	Real-Time System	Location-Aware	Role-Based Platform	Redistribution Integration
Waste Treatment [1–5]	Yes	No	No	No	No
Demand Forecasting [6, 17]	Yes	No	No	No	No
Redistribution Logistics [20–25]	No	Partial	Partial	No	Yes
IoT / Blockchain Systems [11]	Yes	Conceptual	Partial	No	Limited
Proposed System	Yes	Yes	Yes	Yes	Yes

Table 1 highlights the limitations of existing research in food waste management. The previous studies focus on isolated aspects such as waste treatment, demand forecasting and redistribution logistics lacks integrated, real-time and role-based system. The proposed system uniquely combines machine learning-based prediction with location-aware food redistribution in a deployable platform. This comparison clearly highlights that existing studies fails to combine proactive waste prediction with real-time, location-aware redistribution in a deployable role-based platform is resolved in the proposed system.

3. Proposed System

The proposed method provides a detailed, actionable way to reduce food waste using smart forecasting and real-time redistribution. It combines machine learning-based predictions of waste, along with a comprehensive, location-driven redistribution system. It works on the principles of four primary steps include data preparation, preprocessing and training a machine learning algorithm, performing inference to help in decision-making and implementing it into real-time processes.

3.1 Data Collection and Preprocessing

Data collection of donors is obtained using a web interface. These inputs include different parameters of the food such as the type of food, quantity, estimated number of guests, event data, storage requirements whether the item is seasonal or not, the method of preparation, the location of the item and the price. All of these parameters provide input to a raw feature vector, which can be expressed as:

$$x = [x_1, x_2, \dots, x_n] \tag{1}$$

where,

- x represents the raw input feature vector,
- x_i denotes the i^{th}feature collected from the donor through the web interface,
- and n represents the total number of input features describing the food item.

In this case, each xi represents a characteristic data point obtained from the user interface.

The given set of data contains both numerical and categorical attributes, it is necessary to be pre-processed. The numerical attributes are standardized based on the z-score. Normal encoding is the method used to encode category characteristics. For a numerical attribute, let μ and σ represent the mean and standard deviations. The encoded numerical attribute xi' can be obtained based on the formula:

$$x_i' = (x_i - \mu) / \sigma \tag{2}$$

where,

- x_i represents the original numerical value of the i^{th} feature,
- μ denotes the mean of the corresponding feature values in the training dataset,
- σ represents the standard deviation of that feature,
- and x_i' denotes the standardized value obtained after z-score normalization.

This preprocessing method can be reused and a duplicate of this method will be stored/serialized during inference. Based on this stored method, the input to the model becomes a preprocessing feature vector.

3.1.1 Estimation of Target Waste Variable

The target variable for model training represents the actual quantity of food wasted. This value was estimated using post-event donor feedback and historical records, where donors reported the remaining unutilized food after distribution or disposal. The target waste was computed as the difference between prepared quantity and consumed or donated quantity. In case, when real historical data was unavailable, controlled simulation data was generated using domain-informed heuristics based on event type, storage duration, pricing and preparation method. This hybrid approach ensured realistic variance while maintaining consistency with real-world food service behavior. This hybrid estimation approach balances realism and data availability enabling supervised learning while reflecting practical food service behavior.

3.2 Machine Learning Model Design and Training

The machine learning model uses the algorithm of Random Forest regression model. It was adopted based on its ability to handle nonlinearity, ability to prevent overfitting and handling data with varying data types. A Random Forest can be visualized as a collection of decision trees, where each of the trees in the collection is trained on a bootstrap sample of the data. Each tree predicts the amount of wasted food, and the prediction takes the form of an average predictions of the different trees.

Let T = $\{t_1, t_2, \ldots, t_M\}$ be a set of trained trees, where M represents the total number of estimators. For a given input vector x, the predicted waste will be:

$$\hat{y} = \frac{1}{M}\sum_{j=1}^{M} t_j(x) \tag{3}$$

This AI model trains offline using either historical data or artificially generated simulation data. Once the model has been trained, it is saved and loaded into the back-end service for real-time processing. The random forest regression configured 100 decision trees. The maximum depth of each tree was limited to 10% overfitting. Feature sampling performed by the square root method splits each tree as $\sqrt{}$n randomly. This hyperparameters is considered based on cross-validation performance and training stability.

3.3 Inference and Decision Support Mechanism

The given inputs are preprocessed to produce trained data during inference and it executes using random forest model. The user can predict the result in the initial period with the help of proposed work that evaluates the food wastage using computation in percentage format. These predictions are shown in real time on the frontend, thus enabling restaurants to act proactively by adjusting quantities or opting for donations of surplus. When there is excess food, it is stored along with precise geographic coordinates. Available donations can be filtered using the Haversine distance formula implemented in the backend utilities to enable NGOs to redistribute the food efficiently and rapidly.

3.4 System Integration and Operational Workflow

Although JSON-based storage is used for lightweight deployment, scalability is achieved through modular file separation and indexed access using unique donation identifiers. Each donation is stored as an independent JSON object, enabling efficient read and write operations even with thousands of records. Since read operations are localized and non-relational, performance degradation is minimal. For large-scale deployments, the system architecture allows simple transition into document-based databases such as MongoDB without altering application logic. The authentication process depends on JWTs for role-based access control between restaurants, NGOs and administrators. When requests or donations are submitted, automatic emails are sent for real-time coordination. The system allows for a simple and united space where predictions automatically affect redistribution.

3.5 Computational Complexity and Runtime Performance

The preprocessing phase has a linear time complexity is dependent on the number of features. During prediction, a traversal of every decision tree up to depth d is performed for a Random Forest, hence a time complexity of $O(M \cdot d)$, with M denoting the number of trees.

Due to the bounded depth, d, and the fixed value, M, makes the actual time complexity for the prediction phase is maintained to be low. The computation of geospatial distances has a constant time complexity for every donation makes it scalable.

Algorithm 1: Random Forest Training and Prediction Procedure for Food Wastage Estimation

Input: Training dataset D = {(x_i, y_i)}

Output: Trained Random Forest model RF

1: Load dataset D

2: Apply preprocessing to all x_i

3: Initialize Random Forest with M trees

4: for each tree t_j in RF do

5: Sample bootstrap subset D_j from D

6: Train decision tree t_j on D_j

7: end for

8: Save trained RF model and preprocessing pipeline

During inference, the donor-provided feature vector undergoes identical preprocessing as the training data. The processed vector is transmitted through the trained Random Forest model to generate a wastage estimate. This estimate is normalized to prepare quantity and displayed to the user as both absolute and percentage waste.

3.6 System Architecture

The proposed prediction method using random forest and redistribution system designed a modular, scalable, service-oriented platform integrate web technologies with machine learning and external services. The system supports three user roles. They are donors, NGOs and administrators using a web-based interface. A React.js used for frontend to provide role-specific dashboards for creating donation, managing claims and system administration. It will communicate with FastAPI using RESTful APIs to handle authentication, request prediction, workflow donation and administrative operations. The data location was captured using geolocation API and displayed in OpenStreetMap enable distance-aware filtering and map-based donation delivery. A machine learning method embedded in the backend to generate real-time food waste predictions and an SMTP-based notification service sends automated notifications during key workflow events. All system data is stored using lightweight JSON-based storage to ensure simplicity and scalability. Figure 1 illustrates the overall system architecture and their communication.

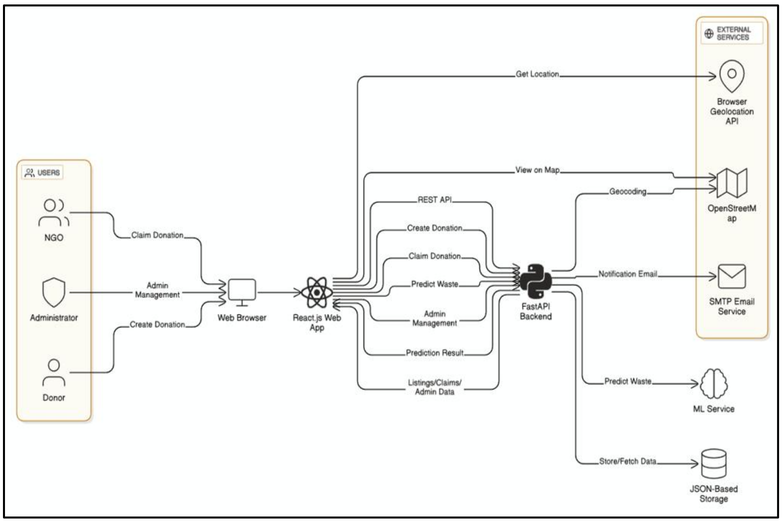

Figure 1. Architecture of the Food Waste Prediction and Redistribution System

4. Results and Discussion

The experimental results of this proposed work focused on the prediction using machine learning models, food donation and system workflow. This method also concentrates on accurate location and overall operation of the system. The accurate prediction of food wastage was improved using feature selection, standard preprocessing approach and ensemble learning. It collects the location type, food price and storage capability to provide high accuracy in real-time.

4.1 Machine Learning Prediction Results

This model uses the machine learning algorithms for accurate food waste prediction. Linear regression, Decision tree and Gradient Boosting algorithms are used and compared for this method. The regression model will calculate the R square error for explaining the variations in food waste data. When compared to the linear regression model, it is failed to handle the non-linear variables like food type, price, storage capacity and event type. This makes linear regression algorithm is not suitable for high accuracy in prediction of food waste.

Ensemble methods can perform better compared to linear regression. Random forest has the high R-square value. This algorithm contains different collection of trees and it is more stable for results. This makes the system to predict the food donation data with varying attributes. Another algorithm Gradient Boosting also give better accuracy. When compared to random forest algorithm, remaining algorithms produce low accuracy. Hence, the random forest algorithm was used for the food waste prediction system. Model performance was evaluated using Mean Squared Error (MSE) and the coefficient of determination (R^2). These metrics are defined as:

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{4}$$

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \tag{5}$$

where y_i is the actual waste, $\hat{y}_i$ is the predicted waste, $\bar{y}$ is the mean of actual waste values, and N is the total number of samples.

The random forest model achieved Mean Square Error (MSE) of 7.37 with a low average deviation between predicted and actual data value. The residual error distribution was zero will suggest unbiased quantities in the dataset. When compared to linear regression and single decision trees, the ensemble approach will reduce the variance and improve the generalization performance.

4.1.1 Estimation Error of Prediction Model

The proposed system uses the random forest model to evaluate estimation error analysis to quantify the deviation between predicted and actual food wastage data values. The estimation error of each prediction evaluate difference between actual and predicted waste data.

$$e_i = y_i - \hat{y}_i \tag{6}$$

Where

- $y_i$represents the actual measured food waste for donation event i,
- $\hat{y}_i$represents the predicted food waste,
- and $e_i$represents the estimation error.

The absolute error per donation event is given by:

$$AE_i = \mid y_i - \hat{y}_i \mid \tag{7}$$

The model achieved an average absolute estimation error of 2.1–3.4 food units per donation event across the evaluation dataset. For medium-scale events (50–200 meal preparation range), the prediction deviation remained within ±8–12% of actual waste demonstrating reliable estimation consistency. The residual error distribution remained zero with low deviation showing that the model does not frequently overestimate or underestimate waste. This confirms that the prediction model provides unbiased and practically interpretable outputs suitable for real-world donation planning.

4.1.2 Strategy Used to Minimize Error Distribution

Several methods are implemented to minimize prediction error distribution and improve model generalization:

1. **Ensemble Averaging (Random Forest):** The multiple decision trees were trained using bootstrap sampling and predictions was average to reduce variance and stabilize outputs.

2. **Feature Randomization:** Random subset selection of features at each split prevented model over-dependence on specific attributes and reduced overfitting.

3. **Bounded Tree Depth:** The maximum depth was restricted to avoid complex trees that memorize training data.

4. **Cross-Validation-Based Hyperparameter Tuning:** The model parameters such as number of estimators and depth were optimized using k-fold cross-validation to achieve balanced bias–variance tradeoff.

5. **Standardized Preprocessing:** Z-score normalization ensured consistent feature scaling, improving model convergence and stability.

These strategies collectively produced a tightly distributed residual error profile with minimal variance across diverse donation scenarios.

4.1.3 Real-World Interpretation of Errors

While Mean Squared Error (MSE) and R^2 provide statistical performance indicators, practical deployment requires interpretation of prediction errors in real-world. Therefore, prediction deviation was evaluated using actual food quantity difference per donation event. On average, the model prediction deviated by 2–4 kg (or equivalent meal units) from actual measured waste for small and medium-scale donation events. For large-scale events such as weddings or community functions, the deviation increased proportionally but remained within acceptable operational tolerance levels for donation planning.

In practical situations, such deviation does not affect redistribution decisions due to donation thresholds operate in larger quantity bands. Hence, the model provides accurate estimates to support proactive donation and waste management.

4.1.4 Error Distribution & Deviation Per Donation Event

Error Distribution Analysis

The distribution of prediction errors was analyzed across multiple donation events to evaluate model stability. Residual values followed an approximately normal distribution near zero indicating unbiased prediction behavior. Most prediction errors were focused within a narrow band of ±3 food units with few outliers observed in cases involving highly irregular event conditions such as unexpected attendance variation or prolonged storage duration.

4.1.4.1 Deviation per Donation Event

For each donation entry, deviation between predicted and actual waste was computed. Observations indicate:

Table 2. Deviation per Donation Event

Donation Event Type	Avg deviation
Small events (<50 meals)	±1.5–2 units
Medium events (50–200 meals)	±3–4 units
Large events (>200 meals)	±5–7 units

These deviations remain acceptable for redistribution planning because NGOs operate with flexible input capacity ranges.

4.1.4.2 Error Distribution Visualization

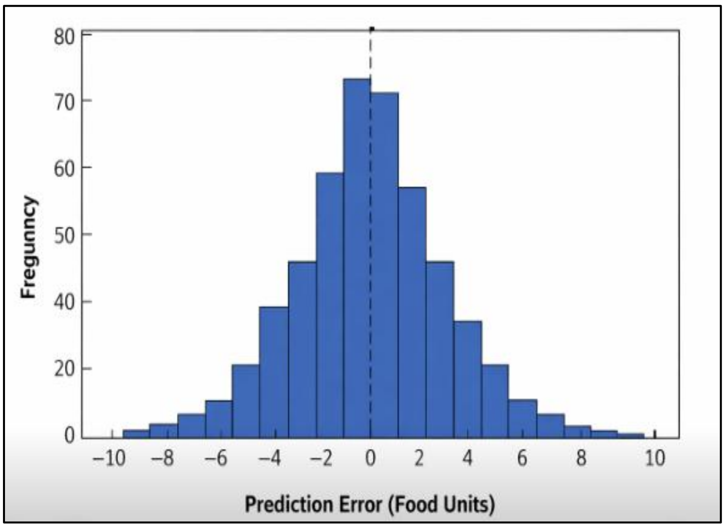

Figure 2. Residual Error Distribution of Random Forest Prediction Model

Figure 2 illustrates the majority of prediction errors cluster near zero, confirming stable and unbiased performance of the model across diverse donation scenarios.

Table 3. Functional Outcomes of the Proposed System

Module	Observed Outcome
ML Prediction Module	Successfully generated real-time wastage amount and percentage
Donation Management	Donations created, stored, and updated correctly
NGO Claim Workflow	Status transition from Pending to Accepted verified
Location Filtering	Distance-based sorting and filtering operational
Notification Service	Automated email alerts triggered on donation claim

Table 3 shows the functional outcomes of the proposed system provides the observed functional performance of each functional core module during implementation. Error minimization was achieved through ensemble averaging, feature randomness, bounded tree depth and cross-validation-based hyperparameter tuning. These strategies collectively reduce model variance and prevent overfitting resulting in a stable and well-distributed error profile.

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4.2 Donation Creation and Redistribution Outcomes

The contribution management flow was analyzed to determine that consistent and accurate system operates from end to end. Donors can rapidly create food donation listings by providing essential food details, including images, specifying dates of expiration and locating specific locations. These donation records saved in the database and immediately display in NGO dashboards so they can quickly access them. NGOs were able to filter positions based on their distance and availability. They could claim appropriate donations in real time.

Each donation status was updated in the system when a successful claim took place. Automated emails sent to donors and NGOs for claim management that make coordination timely and reduced back-and-forth communication. The results demonstrate that the claim workflow works as intended and real-world redistribution could be supported by this platform with no manual steps in its operation.

4.3 Location-Based Redistribution

The location intelligence systems improved the process of allocating donations to NGOs depending on their locations. The use of latitude and longitude for filtering and sorting donations for collection also helped to prioritize items that needed to be collected from the place that they were donated. The program's interactive maps identified the location of the donations and the location of the users, updated the inaccurate assumption about the region being examined. The geographical computations working at the application have minimal cost.

4.4 Overall System Effectiveness and Practical Implications

The platform integrates authentication, prediction, donation management, geolocation filtering and alerting into a single deployable system that converts food waste forecasts into actionable redistribution. Unlike standalone models or static donation systems, it links predictions directly to real-time workflows. Role-based dashboards and administrative controls ensure clarity and governance. It combines ML forecasts with location-aware matching, automated notification and secure access, embedding smart prediction in the donation process. The experiments show that prediction-based workflows reduce food waste with improved accuracy achieved using feature selection, preprocessing and ensemble learning using different variables like event type, pricing and storage conditions.

4.5 Model Accuracy Comparison and Analysis

A comparative analysis of regression-based algorithms was conducted to identify the most accurate model for predicting food wastage. Linear Regression served as the baseline, while Decision Tree, Random Forest and Gradient Boosting were evaluated for their ability to handle nonlinear combination in real-world donation data. Overall results show that ensemble models has better performance compared to Linear Regression. Linear Regression has low performance due to its inability to capture nonlinear dependencies among features such as food type, quantity, event type, and storage conditions. Decision Trees improve performance but are prone to overfitting. Random Forest and Gradient Boosting achieved the highest accuracy, demonstrating better generalization through ensemble learning.

Table 4. Model Performance Metrics

Model	Mean Square Error	R^2 Score
Linear Regression	36.898414	0.644036
Decision Tree	12.744865	0.877049
Gradient Boosting	9.371716	0.907665
Random Forest	7.371716	0.928884

Table 4 provides the evaluated performance metrics of four different models. From that random forest was found to have the best performance.

Unlike gradient-based learning models, Random Forest does not optimize through iterative epochs and therefore does not produce conventional loss or accuracy curves. Instead, model convergence and stability were evaluated using cross-validation performance and residual error distribution, which provides a more appropriate assessment for ensemble tree-based models. Figure 3 compares the prediction accuracy of different ML models.

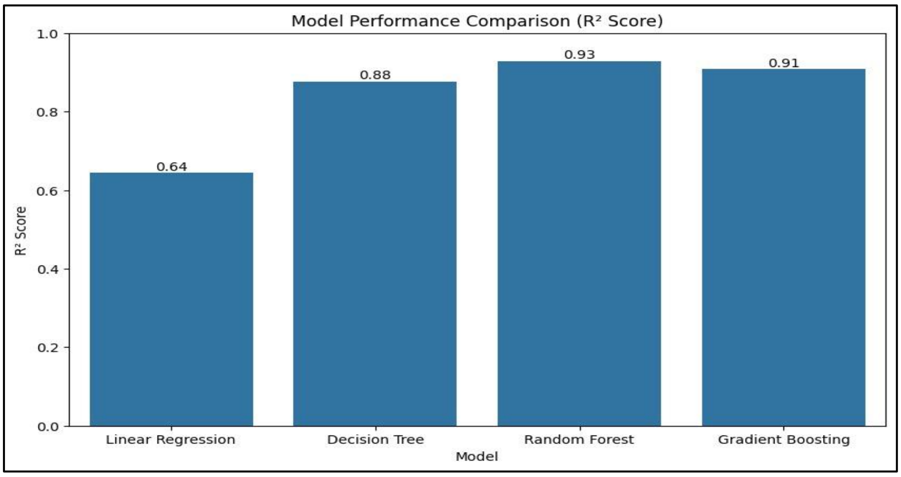

Figure 3. Comparative Accuracy Analysis of Machine Learning Models for Food Wastage Prediction

4.6 Application Workflow and System Usage

The developed web application demonstrates the complete operational workflow of the proposed system. NGOs interact with the platform through a centralized dashboard that provides an overview of available and claimed food donations (Figures 4 and 5). Finally, indicators allow NGOs for rapid assess of redistribution opportunities, while filters based on donation status and geographic distance enable efficient prioritization nearby and time-sensitive donations. The detailed donation dashboard displays key attributes such as food type, quantity, packaging, expiry time, and location to support informed decision-making.

The NGO interface minimizes manual coordination through real-time status updates, location-aware visualizations and automated notifications upon donation claims. The availability of both list-based and map-based views improves situational awareness and enables NGOs to evaluate multiple donation options simultaneously, thereby reducing response time and preventing food spoilage.

On the donor side, AI-driven prediction is integrated directly into the donation workflow. Donors provide contextual inputs such as food preparation method, quantity, pricing and location based on the trained Random Forest model generates real-time food waste predictions. The system presents the predicted waste as both absolute quantity and percentage, along with actionable recommendations to either reduce over-preparation or initiate food donation. This predictive feedback enables donors to make proactive, data-driven decisions depending on post-event waste handling.

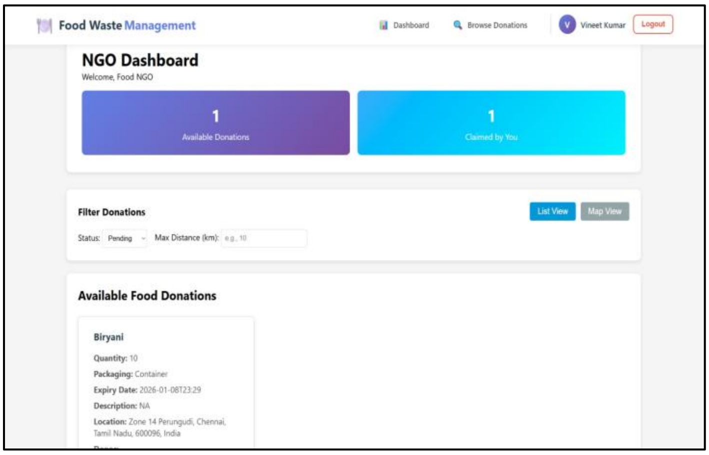

Figure 4. NGO Dashboard Showing Available and Claimed Food Donations

Figure 4 shows the NGO dashboard for the proposed Food Waste Management system. The NGOs have a work on food donations are currently available and the data with claim management. Donation status was filtered and maximum travel distance will assist NGOs to quickly spot suitable donations near their location. The list view provides complete data on each item including food type, amount, packing, expiration date and geographic location. Overall, this interface will help NGOs make rapid and smart decisions while transferring food.

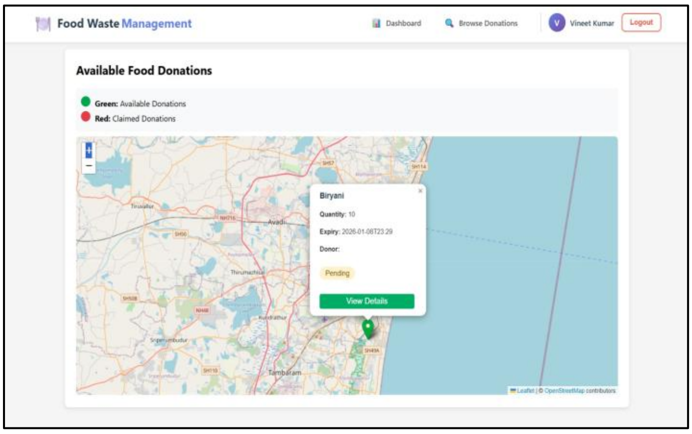

Figure 5. Location-Aware Food Donation Listing for NGOs

Figure 5 below illustrates the food donation map interface accessible to NGO members. NGOs use either the list or map interface to navigate the available food donations. Each food donation is linked to data such as the amount of food donated, packaging information, the time of expiration and the precise address. Location-based sorting allows the

NGO to choose donations based on their locality, thus minimizing transportation time and the risk of food spoiling.

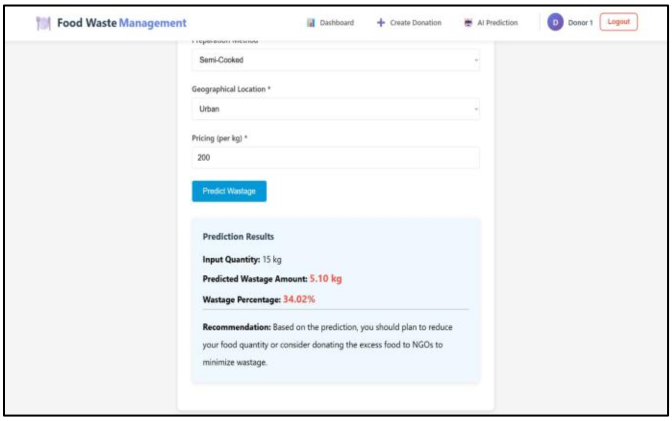

Figure 6. AI-Based Food Wastage Prediction Result Interface

Figure 6 depicts the AI module utilized by donors to predict levels of waste of food within the system. Here, donors provide relevant data regarding the processing of the food, its quantity its price, and through the trained learning algorithm, the predicted quantity of waste is determined. This is shown that the platform has both the quantity of predicted waste and the corresponding percentage of waste providing a recommendation that helps contributors in reducing waste and initiating food contributions.

5. Conclusion and Future Work

This proposed work predicts the food waste and redistributing the food for the hungry people. It combines ML-based waste prediction and using the geolocation for redistributing system. It uses the data preprocessing, random forest and role-based authentication for access the application to work with food donors, NGOs and delivery persons. The result provides advanced notification, accurate data location in real-time. This model is efficient, scalable for the community-based implementation with simplified storage capacities, advanced open-source architecture. In future, this system will be expanded from machine learning method to deep learning method for increasing the accuracy. The users can change the file-based storage into online shared database for analysis in real-time large cities. For policy purposes, combining carbon footprint computation method to encourage donor involvement and make the decisions sustainably.

References

[1] Dehghan, A., Oskoei, V., Khajavi, T., Baziar, M., & Yousefi, M. (2025). Machine Learning-Based Prediction of the C/N Ratio in Municipal Organic Waste. Environmental Technology & Innovation, 37, 103977.

[2] Kravchenko, E., Minkina, T., Privizentseva, D., Zhelnin, M., Bauer, T., Zhao, Y., ... & Shan, S. (2025). Machine Learning Prediction of Biochar Properties Derived from Food Waste. Journal of Environmental Chemical Engineering, 116791.

[3] Lytras, C., Lyberatos, V., Lytras, G., Papadopoulou, K., Vlysidis, A., & Lyberatos, G. (2025). Development of a Model Composting Process for Food Waste in an Island Community and Use of Machine Learning Models to Predict Its Performance. Waste and Biomass Valorization, 16(2), 683-700.

[4] Olawale, R. A., Olawumi, M. A., & Oladapo, B. I. (2025). Sustainable Farming with Machine Learning Solutions for Minimizing Food Waste. Journal of Stored Products Research, 112, 102611.

[5] Guo, Y., Zhao, Y., Li, Z., Wang, Z., Zhang, W., Lin, K., & Zhou, T. (2025). Exploring Interactive Effects of Environmental and Microbial Factors on Food Waste Anaerobic Digestion Performance: Interpretable Machine Learning Models. Bioresource Technology, 416, 131762.

[6] Turker, G. F. (2025). Reducing Food Waste in Campus Dining: A Data-Driven Approach to Demand Prediction and Sustainability. Sustainability, 17(2), 379.

[7] Ramandani, A. A., Chong, J. W. R., Srinuanpan, S., Lim, J. W., Jiang, J. J., & Khoo, K. S. (2025). Artificial Intelligence-Driven Prediction Models for the Cultivation of Chlorella Vulgaris FSP-E in Food Waste Culture Medium: A Comparative Analysis and Validation of Models. Algal Research, 86, 103935.

[8] Suresh, G. H., Varma, G. R. P., Adithya, P. M., Rajesh, C., & Lakshmi, M. A. (2025). Food Waste Management and Prediction Using Machine Learning: A Comprehensive Analysis. IJSAT-International Journal on Science and Technology, 16(2).

[9] Onyeaka, H., Akinsemolu, A., Miri, T., Nnaji, N. D., Duan, K., Pang, G., ... & Chineye, U. (2025). Artificial Intelligence in Food System: Innovative Approach to Minimizing Food Spoilage and Food Waste. Journal of Agriculture and Food Research, 101895.

[10] Han, Y., Zeng, C., Ni, Q., Wang, J., Chu, Z., Zhang, X., ... & Liu, Y. (2025). Time Series Prediction of Anaerobic Digestion Yield and Carbon Emissions from Food Waste Based on iTransformer Model. Chemical Engineering Journal, 163064.

[11] Öztürk, A. B., Heathcote-Fumador, I. E., McSey, I. A., M'Nkubitu, E., Thomi, D., Wainaina, S., & Taherzadeh, M. J. (2025). Food Waste Management Through Machine Learning, IoT, and Blockchain. In Sustainable Technologies for Food Waste Management, CRC Press, 233-262.

[12] Yasin, E. T., & Koklu, M. (2025). A Comparative Analysis of Machine Learning Algorithms for Waste Classification: Inceptionv3 and Chi-Square Features. International Journal of Environmental Science and Technology, 22(10), 9415-9428.

[13] Tun, K. J. G., León-Becerril, E., & García-Depraect, O. (2025). Optimal Control Strategy Based on Artificial Intelligence Applied to a Continuous Dark Fermentation Reactor for Energy Recovery from Organic Wastes. Green Energy and Resources, 3(1), 100112.

[14] Long, F., Xu, M., Liao, W., & Liu, H. (2025). Machine Learning for Predicting and Optimizing the Performance of a Commercial-Scale Anaerobic Digester with Diverse Feedstocks and Operating Conditions. Bioresource Technology, 132940.

[15] Zhao, T., Sun, H., Wang, Y., Zhan, W., Li, Y., Li, W., ... & Tian, Y. (2025). Building the Resilient Food Waste Supply Chain for the Megacity: Based on the Multi-Scale Progressive Fusion Framework. Resources, Conservation and Recycling, 215, 108144.

[16] X. Wang, X. Ming, X. Han, Y. Liu, M. Chen, T. Zhang, and D. Zhang, “Effect of Lactic Acid on Short-Chain Fatty Acids and Hydrogen Production During Anaerobic Fermentation of Acidified Food Waste,” Fuel, vol. 386, 2025, 134275.

[17] M. Rashvand, Y. Ren, D.-W. Sun, J. Senge, C. Krupitzer, T. Fadiji, and H. Zhang, “Artificial Intelligence for Prediction of Shelf-Life of Various Food Products: Recent Advances and Challenges,” Trends in Food Science & Technology, 2025, 104989.

[18] J. C. Lai, Y. L. Then, S. S. Hwang, Y. C. Tam, and C. C. N. Chua, "Modelling Temperature Profiles in Food Waste Composting Using Monod Kinetics," Process Integration and Optimization for Sustainability, 2025, 1–15.

[19] M. A. Suardana and V. Tundjungsari, "Prediction of Waste Volume Based on Annual Trends Using Data Mining," Technovasia, vol. 1, no. 2, 2025, 49–55.

[20] Frerk, M., C. Lünenborg, S. Bornkessel, and M. Speck. "Food redistribution in Germany: implementation and influencing factors." An empirical study based on" Tafel" food banks in Lower Saxony. Er-nahrungs Umschau 72, no. 2 (2025): 34-44.

[21] B. K. Bharatha, "AI-Augmented Redistribution: Human–AI Collaboration to Prevent Waste and Feed Communities," Journal of Computer Science and Technology Studies, vol. 7, no. 10, 2025, 120–127.

[22] Sandoya, J. Chicaiza-Vaca, F. Sandoya, and B. Barán, "A Circular Food Supply Chain Model Using Metro Infrastructure for Food Bank Networks," Sustainability, vol. 17, no. 12, 2025, 5635.

[23] Bonku, Rabiatu, Faisal Alkaabneh, and Lauren Berrings Davis. "Collaborative Vehicle Routing for Equitable and Effective Food Allocation in Nonprofit Settings." Journal of Humanitarian Logistics and Supply Chain Management 15, no. 2 (2025): 135-153.

[24] Pimple, Leena, Sahil Ambulkar, Vishal Sandalwar, Badal Mendhe, and Harshal Dadmal. "Food Donation Management System with Real-Time User Data Tracking by Local Admin." International Journal on Advanced Electrical and Computer Engineering 14, no. 1 (2025): 174-181.

[25] D. Lambert, "'It's All About Sharing': Can circular initiatives be autonomous food spaces?" Journal of Political Ecology, vol. 32, no. 1, 2025.