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Title: Foodhub, Ai Based Smart Surplus Food Redistribution System

Deepika S[1], Aparna D[2], Bharathi GR[3]

Student, Department of BCA, St Francis College, Bengaluru[1]

Student, Department of BCA, St Francis College, Bengaluru[2]

Assistant Professor, Department of BCA, St Francis College, Bengaluru[3]

Email : bharathi.gr7@gmail.com, deepikas5106@gmail.com, aparna0630@gmail.com

Abstract - Food waste is commonly seen in hotels, restaurants, hostels, bakeries, and during functions. During and after events, a considerable amount of food remains, often discarded despite its potential for consumption. At the same time, many NGOs and other organizations need food for people who require it. Often, the main difficulty is finding a quick and convenient way to connect donors with these organizations.

In this paper, we present AI-Based Smart Surplus Food Redistribution System, as a website to simplify this process. A donor can upload information about the available food, including its type, quantity, preparation time, expiry time, and pickup location. The system uses those details to assign a priority to the donation and helps in finding a nearby NGO for collection.

The system also allows users to check the progress of a donation after it has been accepted. Pickup and delivery details can be updated, while QR code verification can be used during the food handover. Donors can also earn reward points when they make successful donations, which encourages them to donate surplus food again. An admin panel is available to manage users, donations and other activities of the website. The system is also designed so that users can access it easily from mobile devices.

The main aim of the proposed system is to reduce the unnecessary disposal of usable food and make the process of connecting food donors with NGOs simpler, faster, and more organized.

Keywords: Artificial Intelligence, Food Waste Reduction, Surplus Food Redistribution, NGO Matching, Sustainable Food Management

1. INTRODUCTION

Food waste is pervasive across the food service and hospitality sector, where hotels, restaurants, hostels and bakeries over-prepare to meet uncertain demand, and where functions, banquets and other organized events frequently leave considerable quantities of edible food. Globally, an estimated 1.05 billion tons of food were wasted in 2022 at the retail, food service and household levels- roughly 19 per cent of all food made available to customers- with food service accounting for 28 percent and retail for 12 per cent of this waste, while a further 13.2 per cent of food is lost in the supply chain between harvest and retail (UNEP, Food Waste Index Report 2024; FAQ, Food Loss & Food Waste).

The central problem is therefore not scarcity but coordination: much of this surplus remains safe and edible for a short window, yet it is discarded because donors have no fast, reliable channel to reach organizations that could use it. In parallel, an estimated 8.2 per cent of the world's population- approximately 673 million people- experienced hunger in 2024 (FAQ). Existing recovery efforts depend largely on informal telephone calls, personal contacts and messaging groups, which are slow, inconsistent and offer no record of quantity, preparation time, expiry time or handover. As a result, donations are missed, collected too late or accepted without sufficient information for the receiving NGO to plan distribution.

This paper presents the AI-Based Smart Surplus Food Redistribution System, a mobile-accessible website that connects food donors with nearby NGOs. A donor uploads the food type, quantity, preparation time, expiry time and pickup location; the system used these attributes to assign a priority to the donation and identify a suitable nearby NGO for collection. Once accepted, the

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donation can be tracked, pickup and delivery details updated, and QR code verification performed at handover, while donors earn reward points for successful donations and an admin panel manages users and platform activity. The system aims to reduce the unnecessary disposal of usable food and make redistribution simpler, faster and more organised.

Key contributions of this paper are:

- A formulation of surplus food redistribution as a time-sensitive coordination and traceability problem rather than a simple listing task.
- A priority assignment mechanism that derives urgency from donor-supplied attributes including food type, quantity, preparation time and expiry time.
- A nearby-NGO matching approach that uses pickup location to route each donation to an appropriate receiving organisation.
- An end-to-end donation lifecycle combining status tracking, handover verification via QR code, donor reward points and an administrative panel.

2.LITERATURE REVIEW

SLNO	Author(s)	Year	Title	Method/ Approach	Key Findings	Limitations/ Gaps
1	Vlachogianni, A.	2026	Food Redistribution:A Case Study on the “Bring It Back” Platform[1]	Case study of a digital redistribution platform	Digital platforms are reshaping how surplus perishable food is redistributed	Single case; no ML model ore metrics
2	Dionisi, L	2026	FoodLink AI: Artificial Intelligence and Digital Platforms for reducing food waste through food redistribution[2]	AI+Digital-Platform concept for redistribution	Concludes that AI-driven platforms can reduce food waste by turning surplus food into organised donations	Conceptual only; no model comparison, dataset or measured accuracy
3	Liu, M. ; Costa, U.	2026	Artificial Intelligence applications for optimizing food distribution and reducing community food waste[3]	Review of AI methodologies for food distribution	Converts ML for demand forecasting and predictive analytics	Preprint- No confirm venue or peer review

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4	Madhu	2025	AI-Driven food packaging Systems[4]	AI-driven packaging / shelf-life intelligence	Describes AI systems predicting shelf life or contamination from historic data and stresses that temperature fluctuations in cold chains drastically affect perishables	Packaging/Sensor-centric: requires instrumentation unavailable to a plain donation web form
5	Seilov,Abildinov and Sutula	2025	Smart innovations in food spoilage detection[5]	ML+Iot sensing (electronic nose); reinforcement-learning agent	Uses food storage conditions and spoilage rates to predict likelihood of spoilage; discusses an RL agent rewarded for actions that preserves shelflife	Depends on IOT hardware that donors do not have; not deployable through a lightweight web API
6	Lytras, Lyberatos and Lytras	2025	Development of a model composting process for food waste in an Island community and use of machine learning models to predict its performance[6]	Five ML models including linear regressions	Employs five distinct ML models to predict values associated with the composting process and accesses feasibility	Treats food waste after disposal (composting), not prevention by redistribution; no urgency classifications
7	Beshiri	2023	Authentication and authorization management in	Access lists and role-based access	Examine authentication and	Enterprise SOA context;no

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			SOA with the focus on RESTful services[7]	control;JWT tokens	authorization for restful services,using access list or RBAC to decide access and JWT as a token format	lightweight application incrementation or domain evaluation
8	Kornienko and Mishina	2021	Principles of securing RESTful API web services developed with python frameworks[10]	Flask RESTful API prototype;JWT as access- control mechanism	Builds a RESTfulAPI in python with flask and adapts JSON with tokens as the main authentication or access-control mechanism	Security-focus; does not address multi-role authorization for a domain workflow such as donation approval
9	Makin and Abdullah	2025	Reducing food waste in culinary institutions[8]	Linear Regression	Argues demand forecasting is vital for minimizing food waste and applies linear regression to inventory management	Linear model with limited capacity for non-linear interactions; institution-scope inventory rather than surplus redistribution
10	Naeem, Isnam, Barua and Araf	2026	A machine learning framework for predicting restaurant food waste to support sustainable food management[9]	ML Framework; demand forecasting under variable conditions	Develops a framework for predicting restaurant food waste and reviews the value of demand forecasting	Predict waste volumes for a business; does not classify donation urgency or serve a donor-facing workflow

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					under variable conditions	

3. METHODOLOGY

3.1 System Overview

FOOD HUB is a Flask-based web application (SQL Alchemy over a relational database, HTML/CSS/JavaScript front end, REST APIs) organised as a sequential pipeline: authentication establishes identity and role, the donation module captures the food record, the freshness module derives a freshness score, the machine-learning module converts it into an urgency class, the matching module ranks recipient organisations, and the NGO, volunteer, and handover, reward and monitoring modules complete the cycle. Only priority prediction is learned from data; freshness, distance and matching use explicit formulas and weighted scoring rules.

3.2 User Registration and Role-Based Authentication

Four roles are supported: Donor, NGO, Volunteer and Admin. Users register with role-specific attributes and log in to an authenticated session. Role-Based Access Control is enforced at the API level: a donor sees only their own donations, an NGO only donations visible to it, a volunteer only assigned deliveries, and the administrator holds system-wide read access.

3.3 Food Donation and Data Acquisition

An authenticated donor submits food name/type, category, quantity, preparation and expiry times, pickup location with latitude and longitude, and an optional description. The record is persisted with a unique donation identifier and creation timestamp, which later stages use to compute donation age and remaining expiry time.

3.4 AI-Based Food Priority Prediction

Priority prediction is the only machine-learning component. A Random Forest classifier is trained on food category, quantity, donation age A, remaining time R and the freshness score F, and outputs one of four classes: Low, Medium, High or Critical. The ensemble of K trees, each trained on a bootstrap sample with random feature subsampling, assigns the majority class:

$\hat{c}(x) = argmax\ over\ c\ \epsilon\ \{Low, Medium, High, Critical\}\ of\ \Sigma\ (k = 1\ to\ K)\ 1[h_k(x) = c]$

The class-probability estimate $P(c \mid x) = (1/K) \cdot \Sigma\ 1[h_k(x) = c]$ gives confidence in the prediction. The predicted class sets the handling order of donations and supplies the urgency term used by matching.

3.5 Smart NGO Matching

Matching is deliberately not a machine-learning model but a deterministic, score-based ranking mechanism. For a candidate NGO n, four normalised components are combined: distance D(n), higher for nearer organisations; requirement fit Q(n) between the food category and the NGO's declared dietary requirements; capacity C(n) for the offered quantity; and urgency U(n), mapped from the predicted priority (Low < Medium < High < Critical). The matching score is the weighted sum

S(n) = w_d D(n) + w_r Q(n) + w_c C(n) + w_u U(n), w_d + w_r + w_c + w_u = 1

Eligible organisations (available capacity, distance within the service radius) are ranked by descending S(n), and the highest-ranked are presented as suitable recipients. Distance used here and in delivery, is the great-circle Haversine distance computed from latitude and longitude (φ, λ) over the Earth's mean radius R. The learned urgency signal is thus one weighted term in the rule-based score; distance, requirement fit and capacity remain purely algorithmic.

3.6 NGO Request and Claim

NGOs view the surfaced donations and request or claim one. The system verifies that the donation is still available and that the NGO is authorised before confirming, after which the donation moves to a claimed state for volunteer assignment.

3.7 Volunteer Delivery and Route/Distance Optimization

A volunteer transports the claimed donation from the pickup location to the NGO. Distance is obtained from the Haversine formula and an estimated travel time is derived as t_travel = d / v_avg is a configurable average speed; no external mapping service or continuous positioning is used.

3.8 QR-Based Handover and Donation Completion

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A QR code encoding the donation identifier is generated at the point of transfer and scanned to confirm the physical handover. Only after the scanned identifier is validated against the database record is the donation marked delivered and the transaction closed.

3.9 Reward System

On successful completion, reward points are credited to the donor's account as a rule-based acknowledgement of the contribution, encouraging sustained participation rather than competitive ranking.

3.10 Administrative Monitoring

Through a centralized interface the administrator oversees users, donations, NGO activities, volunteers, delivery status and overall system activity, so pending claims, incomplete deliveries and anomalies can be identified and resolved.

4. RESULTS AND DISCUSSION

4.1 Model Training Outcome

The food-priority classifier was trained with backend/ml/train/model.py using a RandomForestClassifier over six features (expiry_hours, quantity, food_type, donation_age_hours, storage_condition, food category) with a ColumnTransformer+OneHotEncoder preprocessing stage. Training succeeded and produced three artefacts: the serialised model(food_priority_model.pkl), its metadata (model_metadata.json), and the dataset (training_data.csv).

Metric	Reported Value
Validation accuracy	0.8750 (87.5%)
Training status	Successful; model and metadata persisted
Features	6(3 numerical, 3 categorial)
Output classes	4- Low, Medium, High, Critical

4.2 Food-Priority Prediction API

Post / api / food-priority / predict returns a priority label, confidence and class probabilities (frontend → Flask → validation → ml / predict.py → model). The documented example (expiry_hours = 2, quantity = 10, cooked, age 1 h, refrigerated, non_vegetarian) returned Critical, confidence 0.91; P(Critical/High/Medium/Low) = 0.91 / 0.06 / 0.02 / 0.01. Confidence equals the predicted class's probability – a vote share, not a calibrated score. Incomplete payloads are rejected server-side with the missing fields named, so validation guards the inference path independently of client-side checks.

4.3 End-to-End Functional Results

Using the seeded demo accounts, all four roles logged in (JWT via Flask-JWT-Extended) and reached only their own functions: donors created donations, which received a priority label with confidence; NGOs listed and claimed donations; volunteers managed pickups and delivery status; administrators accessed users, donations, deliveries and analytics – confirming role-based access control is enforced in the running system, not merely declared.

4.4 Automated Testing and Deployment

python -m pytest -q reported 4 passed, 0 failed (tests/test_auth_roles.py, tests/test_food_priority.py; per-module counts and coverage: [insert value]); malformed inputs, expired tokens and concurrent claims are not covered. The Flask backend runs at http://127.0.0.1:5000 (/api/health reachable), the frontend at http://localhost:8000, with SQLite under backend/instance/ via Flask-SQLAlchemy; re-seeding by removing instance/*.db and running python seed.py. Latency, throughput and concurrency were not measured ([insert value] if benchmarked).

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4.5 Discussion

87.5% validation accuracy comfortably exceeds the ~25% random baseline, and tree ensembles are well supported for tabular data of this kind (Grinsztajn et al.; Uddin and Lu; Ali et al.). The model's value is the routing it enables: labels let NGOs triage and volunteers sequence pickups, while the probability vector makes decisions auditable. Caveats: 0.91 is a vote share, not a calibrated probability, and nominal treatment of the ordinal labels penalises a Critical-for-High error like a Low-for-High one. Comparable donor-NGO-volunteer platforms are evaluated mostly functionally; this project's contribution is a trained, API-served, test-validated classifier as a live decision path, though matching remains claim-based unlike Shi et al. 's recommender approaches.

CONCLUSION

FOOD HUB addresses the twin challenges of perishability and coordination through a sequential pipeline: role-based registration, donation capture, freshness analysis, machine-learning priority predication, score-based NGO matching, claim and volunteer delivery, QR-verified handover, reward crediting and administrative monitoring. The design is deliberately hybrid: the Random Forest classifier is the only learned component, converting food category, quantity, donation age, remaining time and freshness score into a four-level urgency class, while freshness quantification, Haversine distance computation and NGO ranking rely on explicit formulas and weighted, rule-based scoring. The predicted priority feeds matching as an urgency term, so the most perishable donations are handled first and matched to the organisation best placed to receive them. Every stage produces explicit, inspectable data and handover is QR-validated, making the loop traceable, transparent and verifiable, while rewards and monitoring sustain participation and oversight. Future work includes real-world deployment, learning the matching weights from historical data, traffic-aware routing, and image-based freshness assessment.

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