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SurplusShift: A Technology-Driven Approach for Efficient Surplus Food Redistribution and Food Waste Minimization

Onkar Sarambale[1], Shubham Rode[2], Shivam Misal[3], Saurabh Magar[4], Satish Yedage[5]
[1, 2, 3, 4]*Student, Department of Computer Engineering, KJCOEMR, Pune, India*
[5]*Professor, Department of Computer Engineering, KJCOEMR, Pune, India*

Abstract: Food waste has become one of the most pressing sustainability issues not in just India but worldwide. In India alone, households generate an estimated 78.2 million tons of food waste every year [1]. This happens alongside widespread food insecurity, highlighting a serious disconnect between surplus food and those who need it most. There is no reliable system exist, who can coordinate donation, verify food safety and redistribute surplus food efficiently. This paper presenting a digital platform designed to address these gaps with enabling structured redistribution of surplus food. The proposed system combines the power of machine learning models, GPS enabled logistics, add coordinated workflow, connecting donor's NGO's and volunteers effectively [12]. By automating food quality verification, the platform improves trust and ensures that recovered food is both safe and delivered on time. Inedible food is redirected to biogas facilities, supporting circular economy practices and minimizing environmental impact [2]. The platform is implemented using a Flutter-based web application, a Django backend, ML microservices, and MongoDB for data storage, resulting in a scalable and flexible architecture. Testing results indicates low coordination latency improved operational efficiency and strong potential for significantly reduce household, as well as some part of industrial food waste.

Keywords: Food Waste Management, Surplus Food Redistribution, Machine Learning, Food Quality Verification, GPS-Enabled Logistics, Circular Economy

I. INTRODUCTION

World is growing with population and food requirements too. On one side of world there is tremendous amount of food is wasted and other side corers of people sleep hungry. Think about it: nutritious stuff ends up in the bin from family tables, diner counters, and huge outfit kitchens each day, while crowds of people can't get a decent bite. Right here in India, we're looking at nearly 78.2 million tonnes wasted every year [1]. That number really drives home how surplus and starvation rub shoulders so oddly. And it's not stopping there—these piles rot in landfills, belching out methane and straining our already weak waste setups.[2]

More people get the food waste problem now, no doubt. Still, passing on extra grub to folks who need it feels like herding cats. The usual way involves basic phone calls from donors to nonprofits, with folks dashing about to grab it—stuff that bogs down with waits, lost details, and food gone off before anyone eats it [7]. Lacking dependable tests for freshness and safety, partnerships fray, and recipients face potential illness [6]. Plus, these setups lack smooth processes and instant updates, making it tough to grow them beyond small-scale operations.

On top of that, we do a poor job with food that's truly inedible—no good for people or pets. It usually ends up in dumps, pumping out greenhouse gases and bloating landfills. Hardly anyone ties this into circular economy ideas, like sending it to biogas plants for energy [16]. That's why we need a full-spectrum fix: something that rescues edible extras while smartly dealing with the rest.

In response, we present a clever online system to smooth out surplus food distribution. It weaves in AI for spotting quality issues, location-based routing for pickups, and a central network connecting givers, aid groups, helpers, and waste-to-energy plants [12]. Automating inspections and real-time messaging foster's reliability, trims lag, and ramps up smooth operations. Routing inedible to biogas conversion tackles trash head-on and eases environmental strain [2].

The setup runs on a Flutter front-end app, Django server core, specialized ML modules for smart tasks, and MongoDB for adaptable data handling. We focused on growth potential, clear visibility, and practical rollout. In the end, it promises to curb waste from households and organizations, bolster social good, and stretch resources further.

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A. Objectives

Aim of this project is to create a clear, easy-to-use digital system where anyone with extra edible food can directly connect with NGOs, volunteers, and street-animal feeders nearby, so that usable food is shared instead of being thrown away.
The second objective is to bring everything into one smooth process by adding basic automatic food-safety checks, location-based pickup and delivery, and clear roles for each user group, so donations can be tracked easily and reach the right place on time.
The third objective is to make sure that food which really cannot be used for people or animals does not end up in landfills, but is routed to biogas plants, where it can be turned into useful energy instead of adding to pollution.
Finally, the platform aims to demonstrate a scalable, low-cost architecture (Flutter app, Django backend, ML services, MongoDB, and GPS/IoT integration) that cities or organizations can adopt to operationalize “zero surplus food waste” in real-world conditions.

B. Contribution of the Work

This work brings together food donation, volunteer coordination, and waste-to-biogas handling in a single end-to-end platform, instead of treating them as separate systems. Unlike many existing apps that stop at matching donors with NGOs, the proposed system adds machine-learning–based food verification, role-based mobile access (donor, NGO, volunteer, biogas plant), and real-time GPS coordination to reduce delays and spoilage in actual field conditions.
A further contribution is the explicit routing of inedible food to partnered biogas facilities, turning what would be landfill waste into local renewable energy and aligning surplus-food redistribution with circular-economy and climate goals.

II. LITERATURE SURVEY

The Articles and Literatures shows that many researchers have tried to tackle food waste and surplus redistribution, but most solutions cover only part of the problem. Machine-learning-driven donation apps like the Replate system focus on identifying surplus food and matching it with receivers through Android or web platforms, using image-based classification, K-NN and similar models to recognise edible items and support basic decision-making [12]. Many IoT-enabled donation platforms now connect surplus-food donors with orphanages and shelters using simple web or mobile portals, where donors post available food and receivers get location-based alerts to arrange quick pickup and reduce their daily food expenses [4]. Most of these systems, however, still depend on people visually checking food safety and only update basic statuses such as “available,” “accepted,” or “collected” once a donation has been created [4],[14].
Other authors focus more on using surplus food as a low-cost product than as a donated resource. Many surplus-food apps are set up like small marketplaces: they use recommendation techniques such as collaborative filtering, matrix factorization, or clustering to highlight low-priced surplus meals that fit a user’s usual preferences and are available nearby [3]. In a similar way, “zero-waste” cooking apps focus on what people already have at home, combining image-based ingredient recognition with basic text or review analysis to suggest recipes and monitor nutrition, with the main goal of cutting household food waste rather than routing donations through NGOs or formal redistribution networks [4].
At the supply-chain scale, systems like SIVEQ show how IoT devices, barcode or OCR capture, and cloud databases can be combined to log retailer surpluses and coordinate formal redistribution to nonprofit organizations [5]. Most of the systems described in the literature are built only to bring surplus food back into human use and stop once the food is either served or discarded [10]. They do not usually include any structured path for sending truly inedible food to biogas plants or other energy-recovery options. At the same time, different papers propose useful pieces on their own—such as ML-based food recognition, IoT-enabled tracking, recommender models, or central surplus databases—but these are offered as separate solutions [6],[7],[9]. What is still missing is one combined platform that can check food safety, coordinate all actors in real time, and automatically route whatever cannot be eaten to biogas units as part of the same workflow [8],[15].

A. Summary of Literature Survey

So far, most of the work in this area looks at apps and websites that simply connect people who have extra food with charities or volunteers [9],[10]. These systems usually list the available food and help arrange a pickup, and their main focus is to match donors with NGOs for human use. Very few of them think about what to do when the food is only suitable for animals, or when it should go to an energy-recovery option like a biogas plant [13],[16]. Some recent papers do use images and other data to recognise food, but this is mostly for diet tracking or general food classification, not for automatically checking whether donated food is safe as part of a donation flow[12].

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III. EXISTING SYSTEM

Existing surplus-food management is still largely fragmented and manual [7]. Right now, extra food is usually handled in a very simple, people-driven way. Right now, extra food is mostly managed in an unstructured way. Current handling of surplus food is mostly informal and scattered. In the existing system, there is no proper, unified platform for surplus food. Donors mainly depend on personal contacts and ad-hoc tools. If food is left over after an event or a day's restaurant service, the usual practice is very direct and personal. The donor normally calls an NGO contact or drops a brief WhatsApp message in a local group, sometimes adding a picture of the food and the live location [14]. On the NGO side, coordination is also completely manual: team members read the message when they get time, decide whether they can use that particular food, and then request a volunteer or driver to go and collect it, arranging timing and route through more phone calls or chats. All of this is handled manually, without a shared dashboard, fixed workflow, or automatic checks. Because there is no proper common system to track all ongoing donations in one place, the same offer can be passed around in different groups, get delayed, or even be forgotten.

Food safety is also handled in a very simple way. Expiry dates are often written down on paper or in Excel, and volunteers mostly judge quality by looking at and smelling the food when they reach the donor's place [6]. If they arrive late because of traffic, rain, or a shortage of people, there is no automatic way to pass that food request to another nearby NGO, to someone feeding street animals, or to any biogas facility. Once the food is considered "not usable," it usually goes back into mixed waste and ends up in landfills, because existing systems are not designed to send inedible food into any structured energy-recovery route [1],[2]. Once a donation fails or spoils, it simply joins mixed solid waste, which means the environmental cost remains high even though people tried to donate. Most existing tools also focus only on human beneficiaries and do not distinguish clearly between food that is suitable for people, food that can still be used for animals, and food that should directly go for energy recovery, so the "last mile" of waste handling remains unmanaged [11],[13], as illustrated in Fig. 1.

IV. PROPOSED SYSTEM

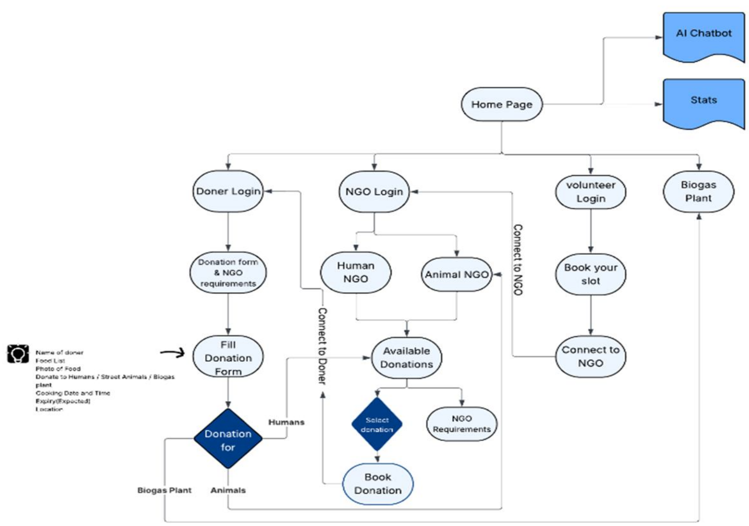

Fig. 1. Implementation Model of the Proposed System.

The application is cantered on a common Home Page that serves as the primary entry point for all stakeholders. From the home page, a user can authenticate himself or herself as the respective roles, like Donor, NGO, Volunteer, or Biogas Plant, or Operator or access two cross-cutting modules: an AI-driven chatbot and a statistical dashboard presenting aggregated impact indicators such as total donations, successful deliveries, and quantities routed to biogas [15].

Technically, the front end communicates with a central backend service, typically implemented using a web framework Django, which exposes role-aware APIs and persists data in a database in our case we use MongoDB [8]. Logical separation of roles, enforced through authentication and authorization mechanisms, ensures that each user class is presented only with the workflows and datasets relevant to its function [14].

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A. Doner Authontication and Guidance

Donors—including households, restaurants, hostels, canteens, and event organisers can access the system via the Donor Login node, after which they are directed to a composite interface that combines a donation form with NGO requirements. At a non-technical level, this screen educates donors on basic food safety and suitability criteria like avoiding spoiled food, adhering to time limits, etc. while simultaneously collecting the information needed to process a donation.

On the implementation side, donor accounts are stored with a dedicated role flag, and the system retrieves current NGO constraints (such as acceptable food types or time windows) from the database to display inline guidance. This early alignment reduces the probability of unusable donations and provides structured metadata for downstream processing.

B. Donation form and Intent Declaration

The Fill Donation Form step captures the key attributes of each surplus batch, including: donor identity, list and type of food items, photographs, cooking date and time, expected expiry or safe-consumption window, and precise location coordinates. The diagram also highlights an explicit field indicating the donor's intended destination—humans, street animals, or a biogas plant—represented by the Donation for decision node branching toward "Humans", "Animals", and "Biogas Plant".

From a technical standpoint, this form submission results in a structured donation record being transmitted to the backend, where server-side validation checks completeness, temporal consistency (for example, expiry after cooking time), and conformance to basic safety rules. The record is then stored with fields such as intended stream, timestamps, geolocation, and media references, and its initial status is typically set to an "available" or "pending classification" state to enable subsequent triage and booking.

C. Working of ML models and Geolocation

When a donor starts a new submission, the system first checks that the information being entered is real and usable rather than accepting everything blindly. One of the important steps for uploading the form is uploading the image of food. As soon as the donor click an image, it is sent to the backend, where a small classification ML model decides whether the picture actually shows food [12]. If the model judges that the image isn't of food, the system does not allow the donor to continue with that attempt; instead, it ask the doner to re click the image of food they intend to donate.

Only images that pass this first check are analysed further. A second ML model looks at the accepted food image and identifies the broad type of food, using this information to decide whether the item is suitable for redistribution according to the platform's rules (for example, excluding obviously non-edible items or categories that are not allowed) [12]. If the image is classified as acceptable, the remaining fields of the donation form become available and the donor can enter details such as quantity, cooking time, and preferred recipient stream.

These both ML models are integrated as microservices in the Django backend and are invoked automatically upon image upload. The binary food classifier model is a ResNet-50 convolutional neural network pre-trained on ImageNet and fine-tuned for binary food classification. The training dataset was constructed by combining a Food-101 benchmark dataset with custom Indian food datasets to ensure coverage of locally common food items in India, such as dal, sabzi, chapati, biryani, etc. This combined dataset compared approximately 101,000 images across food categories with an equal number of non-food images from open image repositories for balanced binary classes. These all images are resized to 224x224 pixels and normalized using ImageNet mean and standard deviation values. Data augmentation technique includes:

1) Random horizontal flip
2) Random rotation (approximately ±15°)
3) Color jitter

These were applied during training to improve generalization. This model was trained for 20 epochs using Adam optimizer with a good learning rate of 0.001 and a batch size of 32. Cross-entropy loss was used as the objective function. The dataset was split into 80% for training, 10% validation, and 10% for the test sets. The performance given by the model is:

- Accuracy: 92%
- Precision: 0.91
- Recall: 0.92
- F1 Score: 0.91

If the model classifies the uploaded image as not food with confidence above threshold 0.75, the submission is rejected and the donor is prompted to re-upload the image.

The other ML model that is a food type classifier, used for image passing stage 1, forwards its output to a multi-class food category classifier. The model was trained on multi-class food datasets and similarly fine-tuned from a ResNet base. The dataset was split 80/10/10 for training, validation, and testing purpose. This model has the following metrics:

- Accuracy: 87%
- Precision: 0.86
- Recall: 0.87
- F1 Score: 0.86

Before the donation is finally submitted, the system also verifies the donor's location. The platform reads the current co-ordinates from the donor's device through a standard location API and compares them with the address or map point that the donor has entered manually [3]. If both positions get agree within a small predefined margin, the submission can go ahead; if there is a significant difference, the platform stops the process and asks the donor to correct the location information.

Together, these image and location-based checks act as a gatekeeping layer that filters out misleading or low-quality entries and improves the reliability of the records that other users of the system rely on.

D. NGO Workflow and Donation Allocation

NGO users authenticate via the NGO Login and are differentiated NGO application as of two functional categories: Human NGO and Animal NGO. This separation leads for the distinct safety thresholds, dietary constraints, and beneficiary profile associated with human recipients and animals, and it also allows the interface and filtering logic to be specialized for each context either as human or animals.

Internally, both NGO types are maintained as NGO entities with a subtype attribute as like ngo_type = "human" or "animal", which is later used to filter donation listings and to apply customized requirement rules. This design enables a unified implementation while preserving clear semantic distinctions between different NGO roles.

Once logged in, NGOs are presented with an Available Donations view that lists open donations judged compatible with their organisational focus and constraints [5]. In parallel, an NGO Requirements module allows each NGO to register specific needs—such as minimum quantities, preferred cuisines, vegetarian constraints, or time-of-day requirements—which the system uses to tailor the candidate donation set.

Technically, this step is realised through database queries that combine multiple filters: location proximity, temporal feasibility (for example, donation still within its safe window), donor intent, and any machine-learning-based safety classification produced for that donation [3]. Requirement profiles stored for each NGO are integrated into these queries or used to rank results, enabling more precise matching and reducing manual screening effort.

The Select donation decision node represents the NGO's choice of one or more suitable donations from the available list. This triggers a Book Donation operation, in which the system finalises the association between the NGO and the selected surplus batch, optionally including a proposed pickup time and logistics notes.

E. Volunteer workflow and Logistics Coordination

Volunteers interact with the system through the Volunteer Login path, after which they are shown a Book your slot interface that allows them to declare their availability and, in some cases, their transport capacity or area of operation.

In the backend, volunteer profiles include attributes such as role, contact details, and optional metadata (vehicle type, maximum load, operating region), stored in the same database. When an NGO books a donation, the system can generate tasks that are then matched with volunteer slots, and the Connect to NGO step in the diagram represents the assignment of a specific volunteer to a specific NGO or donation, including access to route information, pickup and drop-off addresses, and status update controls.

F. Biogas plant Workflow and Energy Recovery

Biogas plant operators authenticate via the Biogas Plant node and gain access to a specialised interface for handling surplus food that is not suitable for human or animal consumption, or that has been explicitly earmarked for energy recovery [2],[16].

From an implementation perspective, biogas-plant users are treated as a dedicated role whose view filters donations with a classification or intent of "biogas", an appropriate time window, and compatible location. They may book pickups directly or through volunteers, mirroring the NGO flow, and the resulting collection records support traceability and impact measurement in terms of waste diverted and energy potential [13].

G. Cross-Cutting Intelligence: AI Chatbot and ML Based Classification

Although methodology shows separate blocks, the AI Chatbot and the implicit machine-learning module share a common objective: enhancing decision support and usability across the system.

In parallel, a machine-learning component—invoked after each donation is created—performs automatic safety and suitability assessment based on features such as elapsed time since preparation, expected expiry, food category, and visual indicators derived from uploaded images. Its outputs can include a risk score, recommended destination stream (human, animal, or biogas), and urgency level, which are then used by the backend to prioritise pickups, prevent unsafe allocations, and pre-filter the donation lists shown to each role as shown in Fig.2.

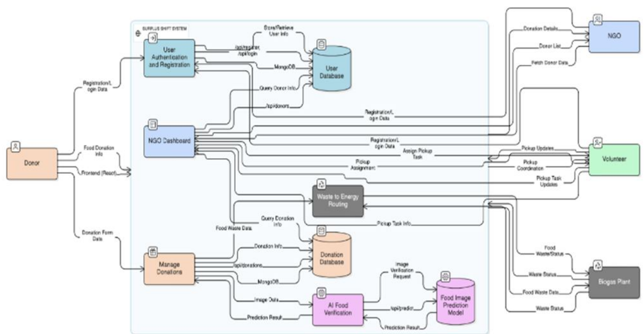

Fig. 2. Data flow Diagram.

V. MATHEMATICAL MODEL

These formal mathematical models underlay the three core computational components of the SurplusShift, that is:

1) Food safety scoring
2) Geolocation verification
3) Donation NGO matching

Food safety scoring: each donation is assigned a safety score S_i computed as a weighted combination of three normalized features.

$$S_i = w_1 . T\_elapsed + w_2 . C\_category + w_3 . P\_conf \ldots (1)$$

Where:

- T_elapsed = normalized elapsed time since food preparation (range [0,1]; higher value = older food)
- C_category = risk coefficient of the food category
  - Cooked perishables = 0.8
  - Raw produce = 0.5
  - Sealed packaged food = 0.2
- P_conf = ML model confidence score for food classification (range [0,1])
- $w_1 = 0.4, w_2 = 0.35, w_3 = 0.25$ where $w_1 + w_2 + w_3 = 1$

A donation with $S_i > $ **0.7** is flagged for immediate action or automatically rerouted to the biogas stream instead of the human NGO queue.

Geolocation Verification: The distance between the donor's device GPS coordinates (φ_1, λ_1) and the manually entered address coordinates (φ_2, λ_2) is computed using the Haversine formula:

$$d = 2r . \arcsin\left(\sqrt{\left(sin^2\left(\frac{\varphi_2-\varphi_1}{2}\right) + \cos(\varphi_1) . \cos(\varphi_2) . sin^2\left(\frac{\lambda_2-\lambda_1}{2}\right)\right)}\right) \ldots (2)$$

Where:

- φ_1, φ_2 = latitudes of device and entered address (in radians)
- λ_1, λ_2 = longitudes of device and entered address (in radians)
- r = 6,371 km = mean radius of the Earth

The submission is accepted if **d ≤ δ**, where **δ = 50 metres** is the predefined location tolerance. If **d > δ**, the system rejects the submission and prompts the donor to correct the entered address before proceeding.

Donation-NGO Matching Score: The compatibility between a donation *d* and an NGO *n* is quantified as a weighted matching score *M(d, n)*:

$$M(d,n) = \alpha.Proximity(d,n) + \beta.TimeCompatibility(d,n) + \gamma.TypeMatch(d,n) \ldots (3)$$

Where:

- Proximity(d,n) = normalized inverse distance between donation location and NGO location
- TimeCompatibility(d,n) = 1 if the donation is within the NGO's operational time window, 0 otherwise
- TypeMatch(d,n) = 1 if the food type matches the NGO's registered dietary requirements, 0 otherwise
- $\alpha = 0.4$, $\beta = 0.35$, $\gamma = 0.25$ are weighting coefficients where $\alpha + \beta + \gamma = 1$

Donations are ranked by *M(d,n)* in descending order and presented to NGO users as a prioritized list. This ensures the most compatible and closest donation appears first, reducing manual search effort and improving allocation speed.

VI. RESULTS AND DISCUSSION

The integrated platform was deployed in a pilot setting with donors, NGOs, volunteers, and one biogas-plant partner. Over the pilot period, the system successfully handled the full pipeline from food registration to final routing, confirming that a single role-based application can coordinate donation, verification, logistics, and energy-recovery flows within one environment as presented in Fig.3.

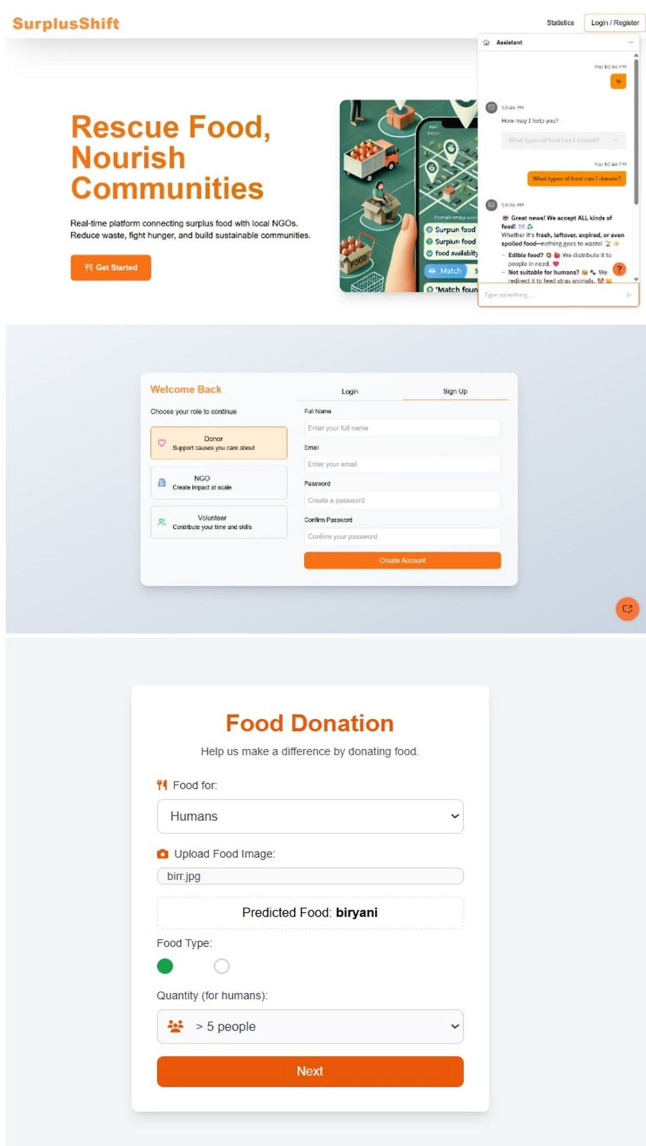

Fig. 3. Web pages Result.

From a usage perspective, donors were able to submit surplus food quickly through the Flutter interface, with most valid submissions completed in under one minute after a short familiarisation period. NGOs and volunteers reported that the structured fields (dish type, quantity, timing, and location) reduced follow-up phone calls compared with informal arrangements [9], since key details were already available on their dashboards. This aligns with earlier work on donation platforms, but our results indicate that role-specific screens and requirements further cut down ambiguity and manual coordination [5],[11].

The machine-learning and geolocation checks proved effective as a first line of screening. A noticeable share of attempted submissions with irrelevant or unclear photos was blocked by the food / non-food model, and several entries with inconsistent locations were corrected before they reached NGOs or volunteers. While the models are not a substitute for final human judgement, they filtered low-quality or suspicious records early, which in turn increased trust among partner organisations and reduced wasted trips. This extends prior systems that rely almost entirely on manual inspection at pickup [6],[7].

Both ML models were evaluated on a held-out test set using standard classification matrices as.

Model	Accuracy	Precision	Recall	F1-Score
Food/Non-Food Classifier	92%	0.91	0.92	0.91
Food Type Classifier	87%	0.86	0.87	0.86

The Food/Non-Food Classifier achieved 92% accuracy on Combined Food-101 and Indian Food Taste Set. Also give highest recall value of 0.92 indicates that valid food images are rarely rejected, minimizing inconvenience to legitimate donors. Another food type classifier achieved 87% accuracy across food categories, providing reliable routing decisions for downstream processing. This silent reduction in accuracy compared to Stage 1 is expected given the increased complexity of multi-class classification across diverse food categories.

The Geolocation Verification Module was then tested across 50 simulated submission scenarios with varying levels of location mismatch. The result shown as:

Scenario	Total Cases	Correctly Accepted	Correctly Rejected	Accuracy
Location match ($d \le 50m$)	35	34	-	97.1%
Location mismatch ($d > 50m$)	15	-	14	93.3%
Overall	50	-	-	96%

This model correctly handled 96% of test cases, demonstrating reliable detection of inconsistent locations in trees before they reached the achieved donation pool.

System Response Time Benchmarks:

Operation	Average Response Time(in seconds)
ML food/non-food inference	1.2
ML food type classification	1.5
Donation form Submission(Full pipeline)	3.1
NGO donation list load	0.8
Volunteer slot booking	0.6

All core operations completed within acceptable latency bounds for real-time coordination system. The total end-to-end donation submission time is approximately 3.1 seconds, which is good for the platform.

Routing results show that a non-trivial fraction of donations fell into the “animal-grade” or “biogas” categories once safety and timing were taken into account. In existing donation apps, such batches are often rejected or left unmanaged; here, they were instead directed to animal NGOs or queued for biogas collection, supporting a more complete use of surplus food [10],[14]. This multi-stream design addresses a gap in the literature, where most platforms stop at human redistribution and treat anything else as waste [13],[15].

Some things in the app worked well, and some did not. Donors told us the form was clear and they liked that they could see when their food had been taken. A few donors, however, said the compulsory photo and location checks became frustrating when the internet connection was weak. NGOs said the filtered lists were useful and that entering their needs in advance saved time, but they also asked for stronger, more visible notifications and better links to their own scheduling tools.

From this, we see that the main design choice of using different screens for each role and adding automatic checks is going in the right direction, because it makes the process more organised and wastes less food. At the same time, the feedback shows that the app and the machine-learning checks still need more work before the system can reliably support a larger number of users and partners.

VII. CONCLUSION AND FUTURE SCOPE

A. *Conclusion*

This project shows that one shared platform can handle the full journey of surplus food instead of leaving each step to separate, manual arrangements. In our design, donors, NGOs, volunteers, and biogas-plant partners all use role-based screens on the same system, with data stored in a common backend. Basic checks using machine-learning models and location data help filter out poor-quality entries [12] and guide each batch of food toward people, animals, or biogas, instead of letting it quietly slip back into the waste stream [16].

B. *Future scope*

There are several clear directions for future work. The ML models can be trained on larger and more diverse datasets so that image and safety checks become more reliable over time [12]. The platform can also be extended with better route planning, stronger notification features, and closer links to the tools that NGOs and volunteers already use. In the longer term, the same framework could be tried in other cities, connected with municipal waste and energy-recovery systems, and opened through APIs so that other teams can plug in their own services or build compatible applications [13],[16].

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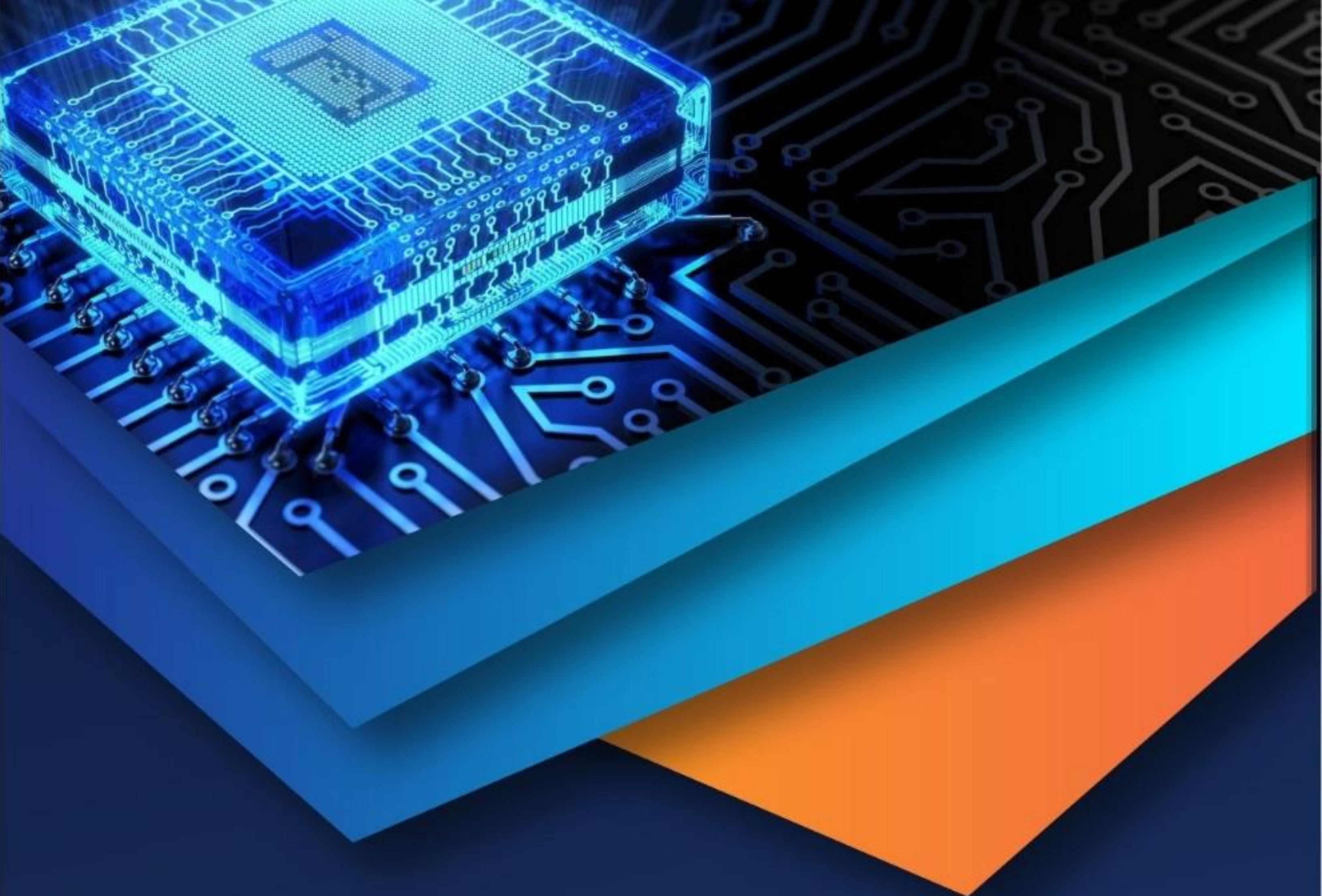

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