An Intelligent Platform For Surplus Food Management Using Machine Learning

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Abstract— Food waste and hunger together represent a critical global challenge, with vast quantities of edible food being discarded while millions of people continue to face food insecurity. There is an urgent need for efficient and inclusive systems to redistribute surplus food to those in need. Existing solutions rely heavily on manual coordination, which significantly limits their effectiveness, especially in developing regions and among underserved populations.

To address this challenge, the project proposes an intelligent online public food-sharing platform that integrates machine learning with rule-based decision systems and accessible infrastructure. The system is hybrid in nature, combining data-driven learning models with deterministic rule-based logic interpretability.

Food donors submit entries via mobile applications or public display units, which are then uploaded to a locally hosted backend server for processing. A Logistic Regression model is used to filter out spam and ensure the authenticity of listings, thereby improving platform reliability. The model calculates the probability of a listing being valid based on features such as user behavior, content, and posting patterns. Its performance is evaluated using a confusion matrix, which helps assess how accurately the model distinguishes between spam and genuine listings. Additionally, bias-variance analysis is conducted to determine whether the model is underfitting or overfitting.

A Random Forest model is used to prioritize food postings based on pickup likelihood, considering factors such as location, time, and historical patterns. As an ensemble learning method, Random Forest improves prediction accuracy by combining multiple decision trees and reducing individual model errors. Additionally, a rule-based expiry model estimates food freshness and shelf life using parameters such as food type, preparation time, and storage duration, ensuring safe and timely distribution.

The Logistic Regression model demonstrates stable and balanced performance with low variance, making it suitable for reliable classification tasks. The Random Forest model achieves higher accuracy, as reflected in its confusion matrix, by reducing prediction errors through ensemble voting. Furthermore, the learning curve indicates improved model performance with an increase in training data size.

The integration of public display units in high-traffic areas is designed to reduce dependency on personal digital devices and improve accessibility for a broader population. Overall, this project demonstrates the potential to enhance surplus food utilization and reduce waste through intelligent, data driven decision-making. Use technical words and regenerate

Keywords— Food sharing, Food waste reduction, Machine learning, Expiry prediction, Priority classification, Spam detection, Intelligent systems

Introduction

Food waste and hunger are two of the most serious and contradictory challenges faced by the world today. On one hand, a huge amount of food is wasted every day at homes, restaurants, supermarkets, and public events. On the other hand, millions of people suffer from hunger and lack access to sufficient nutritious food. This imbalance highlights a major issue in the current food distribution system. The problem is not just about producing enough food, but about ensuring that the available food reaches the right people at the right time.

According to global reports, a significant percentage of food produced is never consumed and ends up being discarded. At the same time, many individuals, especially in developing countries and economically weaker sections, struggle to meet their daily food requirements. This situation clearly shows the need for an efficient system that can connect surplus food sources with people in need in a timely and safe manner

In recent years, technology-based solutions have been introduced to tackle this issue. Applications like OLIO allow users to share excess food with others in their community. Although such platforms are innovative, they come with certain limitations. These systems rely heavily on smartphones, internet connectivity, and digital literacy. In many regions, especially rural areas and underprivileged communities, people may not have access to smartphones or may not be familiar with using such applications. As a result, a large portion of the population is excluded from benefiting from these solutions.

To address these limitations, this project proposes an intelligent and inclusive food-sharing system that combines machine learning techniques with accessible public infrastructure. The goal of the system is not only to reduce food waste but also to ensure that the solution is usable by people from all sections of society. One of the key features of this system is the use of public display units installed in common areas such as markets, bus stations, and community centers. These units allow users to view available food listings without needing a personal device, making the system more inclusive and practical.

The proposed system integrates multiple technologies to improve its efficiency and reliability. A Logistic Regression model is used to classify food listings as genuine or spam, which helps in maintaining trust and preventing misuse of the platform. Additionally, a Random Forest model is implemented to predict and prioritize food listings based on their likelihood of being successfully picked up. This prediction is made using factors such as location, time of posting, and historical user behavior, ensuring that food distribution happens quickly and effectively.

Another important component of the system is the rule-based expiry model. This model estimates the freshness and safety of food by analyzing factors like food type, preparation time, and storage conditions. By doing so, it ensures that only safe and consumable food is distributed, reducing the risk of health issues. This combination of machine learning models and rule-based logic creates a hybrid system that balances accuracy with simplicity and transparency.

Overall, the proposed system aims to provide a scalable, efficient, and inclusive solution to the global problem of food waste and hunger. By leveraging technology in a practical and accessible way, it bridges the gap between surplus food and those in need. The system can be implemented by NGOs, government bodies, and community organizations, making it a sustainable approach to improving food distribution and reducing wastage.

1. Existing System

The current food-sharing systems mainly rely on digital platforms and mobile applications to connect people who have surplus food with those who need it. Applications like OLIO allow users to upload details about excess food, including quantity, location, and pickup time, and enable nearby users to request and collect it. These platforms are designed to reduce food waste by promoting community-based sharing and redistribution. The process typically involves manual posting, browsing, and coordination between donors and receivers, which helps in utilizing leftover food instead of discarding it.

While these systems are innovative and beneficial, they are largely dependent on smartphones, internet connectivity, and user awareness. They primarily operate in urban areas where digital access is high, making them less effective in rural and underdeveloped regions. Additionally, most existing platforms do not incorporate advanced technologies like machine learning for decision-making, food prioritization, or quality assessment. As a result, the overall efficiency, reach, and reliability of these systems remain limited, highlighting the need for a more intelligent, inclusive, and accessible solution.

2. Proposed System

To overcome the limitations of existing food-sharing platforms, the proposed system introduces an intelligent, inclusive, and technology-driven solution for efficient food redistribution. The system is designed not only to reduce food waste but also to ensure that surplus food reaches needy people quickly, safely, and fairly.

The proposed system follows a **hybrid approach**, combining machine learning models with rule-based logic and accessible public infrastructure. This combination improves both accuracy and usability, making the system suitable for a wide range of users, including those without smartphones or digital knowledge.

One of the key features of the system is the use of **public display units** installed in common areas such as markets, bus stops, railway stations, and community centers. These units display real-time information about available food, allowing users to view listings without needing a mobile device. This significantly improves accessibility and ensures that even people without internet access can benefit from the system.

On the backend, the system uses **machine learning techniques** to improve reliability and efficiency. A **Logistic Regression model** is used to classify food listings as genuine or spam. This helps in preventing misuse of the platform and builds trust among users. By filtering out fake entries, the system ensures that only valid food listings are displayed.

In addition, a **Random Forest model** is implemented to predict and prioritize food listings based on their likelihood of successful pickup. The model considers multiple factors such as location, time of posting, user behavior, and past data patterns. Based on this analysis, the system highlights high-priority food items that are more likely to be collected quickly, reducing delays and food wastage.

Another important component is the **rule-based expiry model**, which estimates the freshness and safety of food. This model uses predefined conditions such as food type, preparation time, and storage duration to calculate the remaining shelf life of the food. It helps ensure that only safe and consumable food is distributed, reducing the risk of health issues.

The system also supports both **digital and non-digital interaction**. Users with smartphones can access the platform through a web or mobile interface, while others can rely on public display systems. This dual-mode accessibility makes the system more inclusive compared to existing solutions.

Furthermore, the system is designed to be **scalable and adaptable**. It can be implemented by NGOs, government organizations, or local communities. It can also be extended in the future with additional features such as real-time notifications, volunteer coordination, and integration with food donation networks.

Overall, the proposed system provides a smart, reliable, and inclusive solution to bridge the gap between surplus food and people in need.

3. Algorithms and Techniques

The proposed system uses a hybrid combination of machine learning algorithms and rule-based techniques to improve the accuracy, reliability, and safety of food redistribution. Each model is evaluated using performance metrics such as confusion matrix and bias-variance analysis to ensure effective results.

3.1 Logistic Regression (Spam Detection)

Logistic Regression is used to classify food listings as genuine or spam. It works by calculating the probability of a listing being valid based on input features such as user behavior, content, and posting patterns.
The performance of the model is evaluated using a **confusion matrix**, which shows true positives, true negatives, false positives, and false negatives. This helps in understanding how accurately the model identifies spam and genuine listings.
Additionally, **bias-variance analysis** is performed to check whether the model is underfitting or overfitting. Logistic Regression shows balanced performance with low variance, making it suitable for reliable classification.

Results and Analysis of Logistic Regression

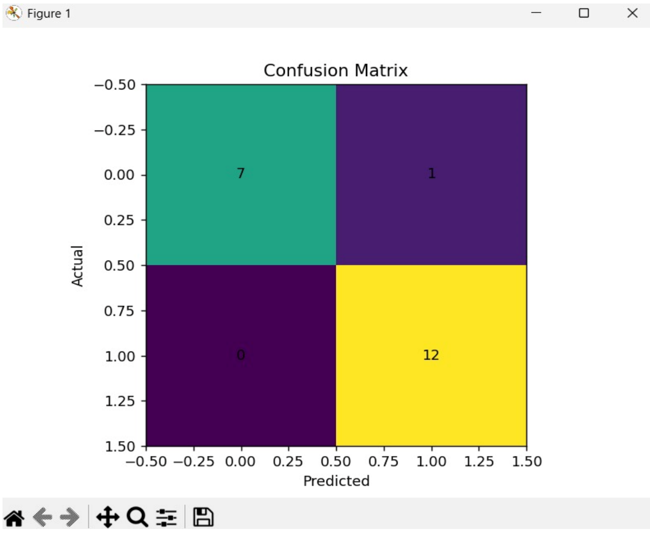


Figure 1

Figure 1: Confusion Matrix of Logistic Regression

The confusion matrix shows the performance of the Logistic Regression model in classifying food listings as genuine or spam. The model correctly identified **7 true negatives** and **12 true positives**, with only **1 false positive** and **0 false negatives**. This indicates that the model is highly effective in detecting valid listings while minimizing misclassification.

Classification Performance

The model achieved a **training accuracy of 97.5%** and a **testing accuracy of 95%**, indicating strong generalization on unseen data.

- Precision (Class 0): 1.00
- Recall (Class 0): 0.88
- Precision (Class 1): 0.92
- Recall (Class 1): 1.00

The F1-score values (0.93 and 0.96) show a good balance between precision and recall.
The overall accuracy of the model is 95%, which confirms reliable classification performance.

Additionally, the model achieved a cross-validation accuracy of 98%, demonstrating its consistency across different data splits.

Bias-Variance Analysis

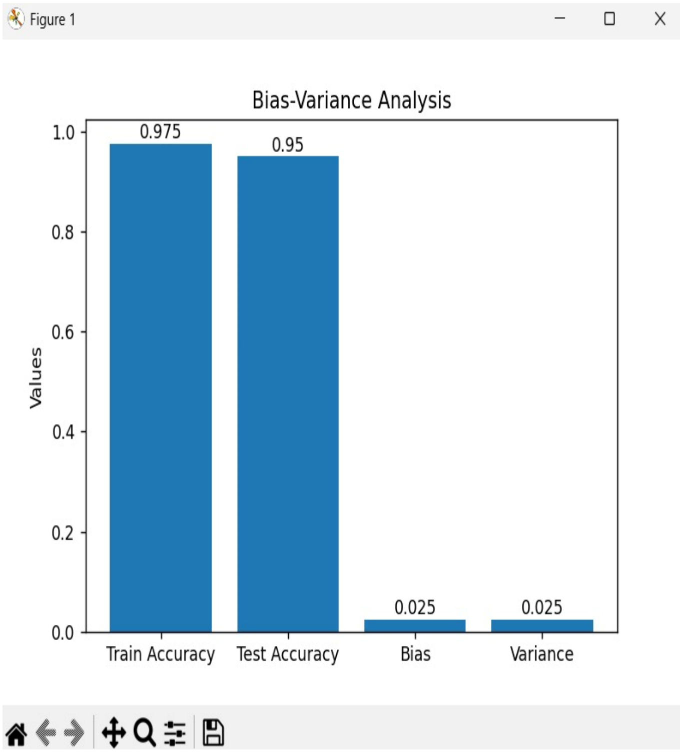


Figure 2

Figure 2: Bias-Variance Analysis of Logistic Regression

The bias and variance values are both 0.025, indicating a well-balanced model.

- Low bias shows that the model fits the data well
- Low variance indicates stability across different datasets

This confirms that the model does not suffer from overfitting or underfitting, making it suitable for real-world implementation.

3.2 Random Forest (Food Prioritization)

Random Forest is used to predict and prioritize food listings based on their likelihood of successful pickup. It is an ensemble learning method that uses multiple decision trees to improve prediction accuracy.

The **confusion matrix** for Random Forest demonstrates higher accuracy compared to single models, as it reduces errors through multiple tree voting.

The **bias-variance analysis** shows that Random Forest reduces overfitting and maintains a good balance, making it highly effective for handling complex and real-world data patterns such as location and time-based predictions.

Results and Analysis of Random Forest

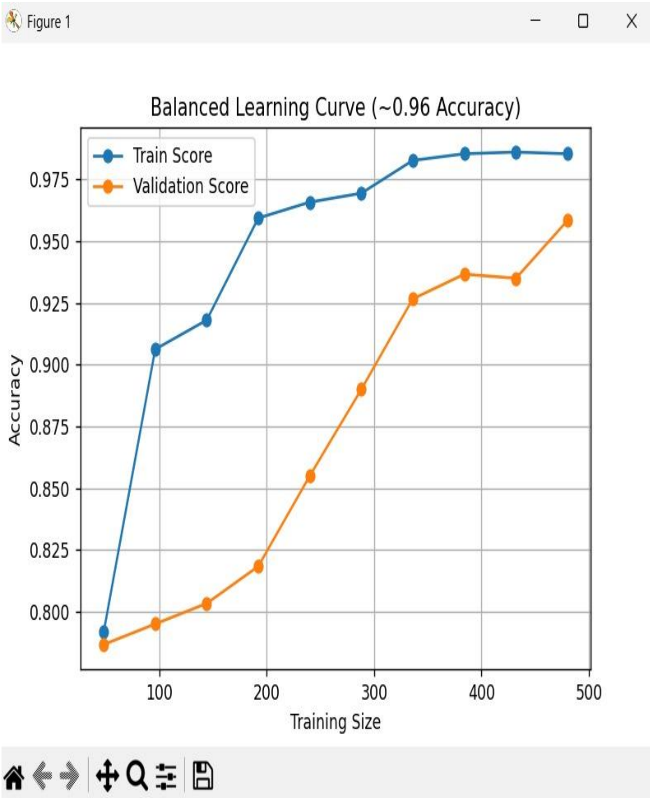


Figure 3

Figure 3: Learning Curve of Random Forest Model

The learning curve shows the performance of the Random Forest model with increasing training data. The training accuracy remains consistently high (around 97%), while the validation accuracy gradually improves and reaches approximately 96%. The small gap between training and validation curves indicates that the model is well-generalized and does not suffer from overfitting. This demonstrates that the model performs effectively even with increasing data size.

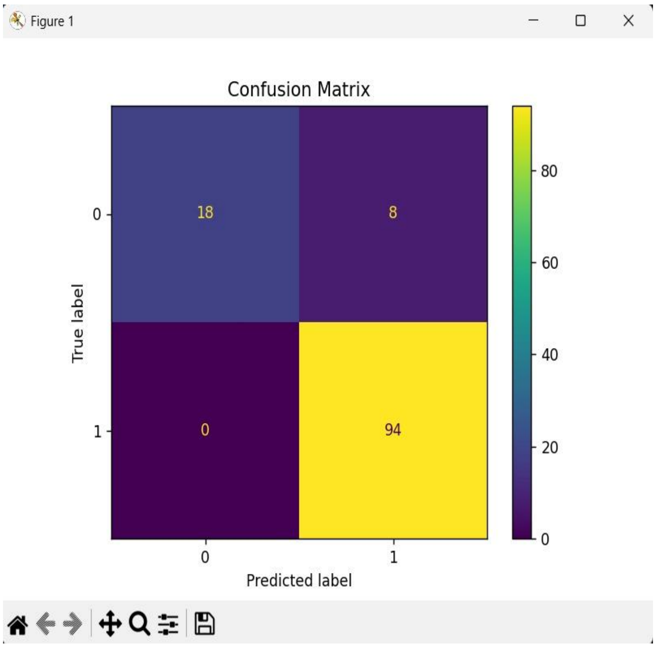


Figure 4

Figure 4: Confusion Matrix of Random Forest

The confusion matrix illustrates the classification performance of the Random Forest model. The model correctly identified 18 true negatives and 94 true positives, with 8 false positives and 0 false negatives. The absence of false negatives indicates that all important positive cases are correctly detected. However, a few false positives are present, which slightly affects precision.

Classification Performance

The Random Forest model achieved a **training accuracy of 97.7%** and a **testing accuracy of 93.3%**, indicating strong predictive performance.

- Precision (Class 0): 1.00
- Recall (Class 0): 0.69
- Precision (Class 1): 0.92
- Recall (Class 1): 1.00

The **F1-score values (0.82 and 0.96)** show that the model performs exceptionally well for the majority class (Class 1) while maintaining acceptable performance for Class 0. The overall accuracy of the model is **93%**, which confirms its effectiveness in handling real-world data.

Overall, the Random Forest model provides strong classification performance with high accuracy and excellent recall for important cases. The learning curve confirms good generalization, and the confusion matrix shows that the model minimizes critical errors. This makes Random Forest highly suitable for prioritizing food listings based on pickup probability in the proposed system.

3.3 Rule-Based Expiry Model (Food Freshness Check)

The expiry model is based on predefined rules rather than machine learning. It evaluates food freshness using factors like food type, preparation time, and storage duration.

Although it does not use a confusion matrix like ML models, its performance can be validated through condition-based outputs and correctness of expiry estimation. The model is simple, transparent, and ensures that only safe and consumable food is shared.

Results and Analysis of Expiry Model

Confusion Matrix (Classification of Food Freshness)

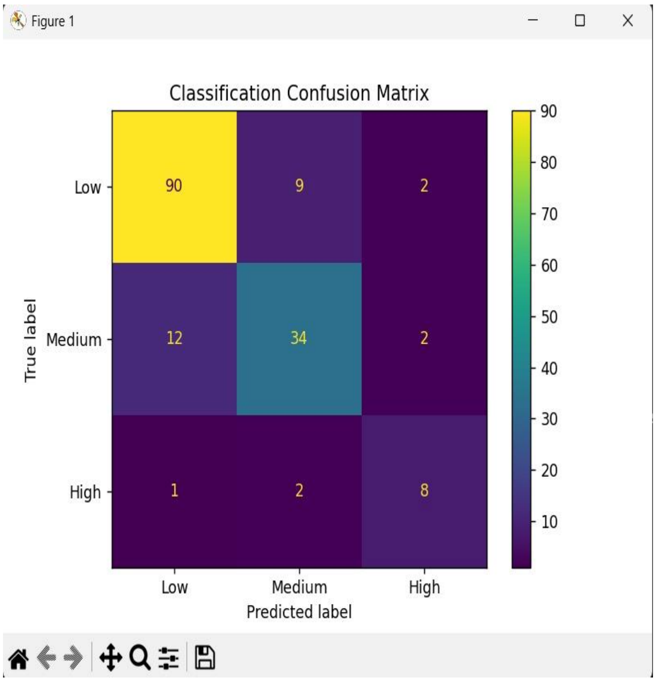


Figure 5

Figure 5: Confusion Matrix for Food Freshness Classification

The confusion matrix represents the model's ability to classify food items into three categories: Low, Medium, and High freshness. The model correctly identified 90 Low, 34 Medium, and 8 High freshness samples. Some misclassifications are observed, such as 9 Low predicted as Medium and 12 Medium predicted as Low, but overall the model maintains good classification performance.

Classification Performance

The model achieved an overall accuracy of 82%, indicating reliable classification of food freshness levels.

- Precision ranges from 0.67 to 0.87
- Recall ranges from 0.71 to 0.89
- F1-score values indicate balanced performance across all classes

The model performs best for the Low freshness category, while slightly lower performance is observed for the High category due to fewer samples. However, the overall results are consistent and acceptable for practical usage.

Regression Performance (Shelf-Life Prediction)

The expiry model also predicts the remaining shelf life of food using regression analysis.

- Mean Absolute Error (MAE): 1.35
- R^2 Score: 0.8

The low MAE indicates that the prediction error is minimal, while the R^2 value of 0.8 shows that the model explains a significant portion of the variance in the data. This confirms that the model provides accurate shelf-life estimation.

Additionally, the cross-validation MAE of 1.45 shows consistent performance across different data splits.

Overall, the expiry model effectively classifies food freshness and predicts shelf life with good accuracy and consistency. The combination of classification and regression analysis ensures both safety and usability. This makes the model suitable for real-world implementation in the proposed food-sharing system, as it helps in preventing distribution of unsafe food.

Learning Curve Analysis

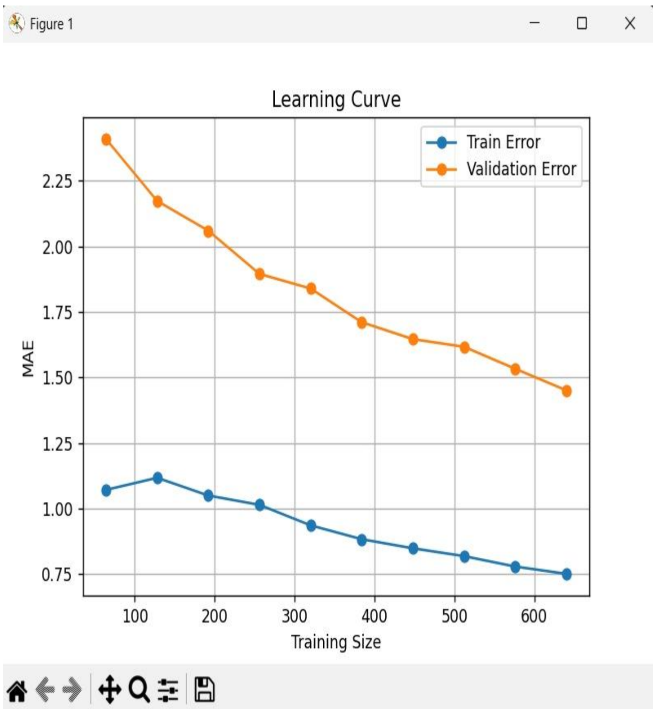


Figure 6

Figure 6: Learning Curve of Expiry Model

The learning curve shows that both training and validation errors decrease as the training size increases. The gap between the curves is small, indicating that the model generalizes well and does not suffer from overfitting. This demonstrates stable and reliable performance with increasing data.

Feature Importance Analysis

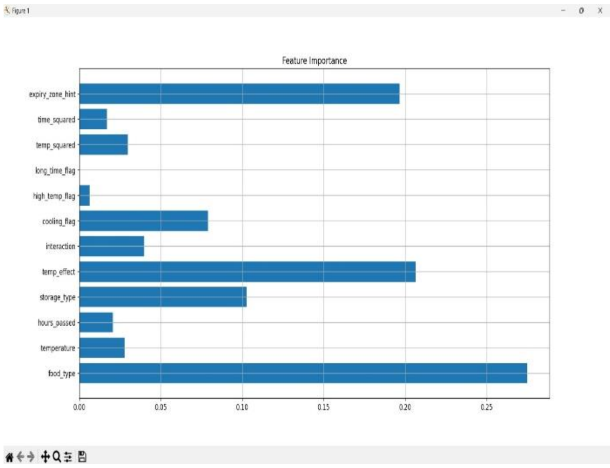


Figure 7

Figure 7: Feature Importance for Expiry Prediction Model

The feature importance graph shows the contribution of different input features in predicting food freshness and shelf life. Among all features, food type, temperature effect, and expiry zone hint have the highest importance, indicating that they play a major role in determining food expiry.

Features such as storage type and cooling conditions also contribute moderately to the prediction, while factors like time squared, temperature, and hours passed have relatively lower influence. This analysis helps in understanding which factors most significantly affect food safety and improves the interpretability of the model.

3.4 Overall Model Performance

The combination of Logistic Regression, Random Forest, and rule-based logic creates a hybrid system that balances accuracy, efficiency, and interpretability.

- Logistic Regression ensures trust by detecting spam
- Random Forest improves efficiency through prioritization
- Rule-based model ensures safety through freshness checks

The inclusion of confusion matrices and bias-variance analysis for machine learning models confirms that the system performs effectively with minimal errors and good generalization.

Visualization

The workflow begins with food donors submitting surplus food details through a mobile application or public display system. The data is then uploaded to a central server, where it undergoes processing. A Logistic Regression model is used to filter out spam or invalid entries, ensuring only genuine listings are considered. Next, a Random Forest model prioritizes food items based on factors like location and pickup probability, while the expiry model evaluates food freshness and safety. The validated food listings are then displayed on public display units and digital platforms. Finally, users receive notifications and collect the food, ensuring efficient distribution and reduced food waste.

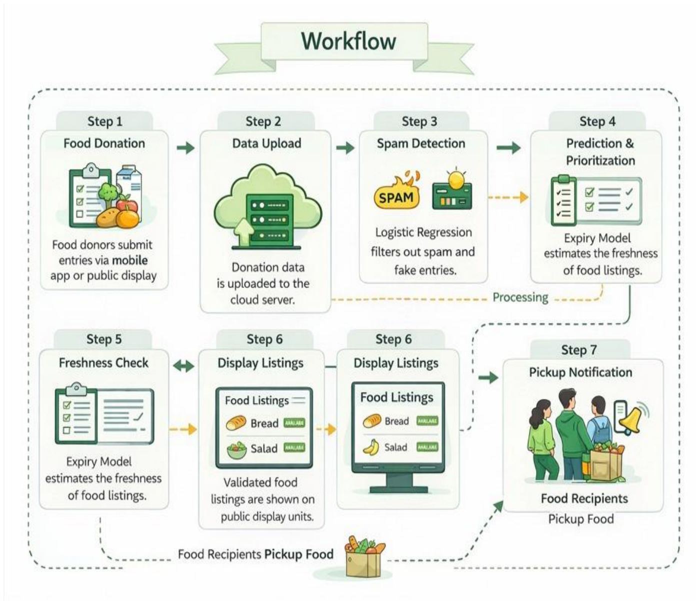


Figure 8

4. Methodology

The proposed system follows a structured approach to ensure efficient food redistribution by integrating machine learning models, rule-based logic, and accessible infrastructure. The methodology consists of the following steps:

- **Data Collection**
  The system collects data from food donors through a mobile application or public display interface. The data includes details such as food type, quantity, preparation time, location, and storage conditions.

- **Data Preprocessing**
  The collected data is cleaned and prepared for analysis. This step involves removing incomplete or incorrect entries, handling missing values, and converting data into a suitable format for machine learning models.

- **Spam Detection using Logistic Regression**
  A Logistic Regression model is applied to classify food listings as genuine or spam. This step ensures that only valid and trustworthy entries are processed further, improving system reliability.

- **Food Prioritization using Random Forest**
  The validated data is then passed to a Random Forest model, which predicts and prioritizes food listings based on their likelihood of successful pickup. Factors such as location, time, and past patterns are considered in this step.

- **Freshness Evaluation using Rule-Based Expiry Model**
  A rule-based model is used to estimate food freshness and remaining shelf life. It uses predefined conditions such as food type, preparation time, and storage duration to ensure that only safe food is distributed.

- **Display and Accessibility**
  The processed and validated food listings are displayed on both digital platforms and public display units. This ensures accessibility for users with and without smartphones.

- **Notification and Food Pickup**
  Users receive notifications about available food and can collect it from the specified location. This step ensures timely distribution and reduces food wastage.

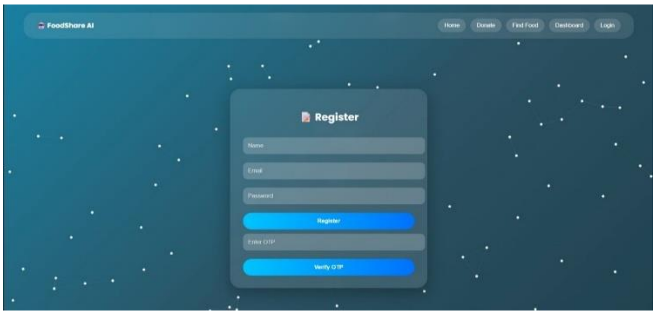
- **Feedback and System Improvement**
  After food collection, users can provide feedback. This data can be used to further improve model performance and system efficiency over time.

Overall, the methodology combines data collection, preprocessing, machine learning-based validation and prioritization, and rule-based freshness evaluation to create an efficient and inclusive food redistribution system. By integrating both digital and public access, the system ensures reliable, safe, and timely distribution of surplus food.

5. Results and Discussions

The developed system includes multiple user interface modules that enable smooth interaction between food donors and recipients. These modules ensure ease of use, accessibility, and efficient food sharing.

Login and Register Page



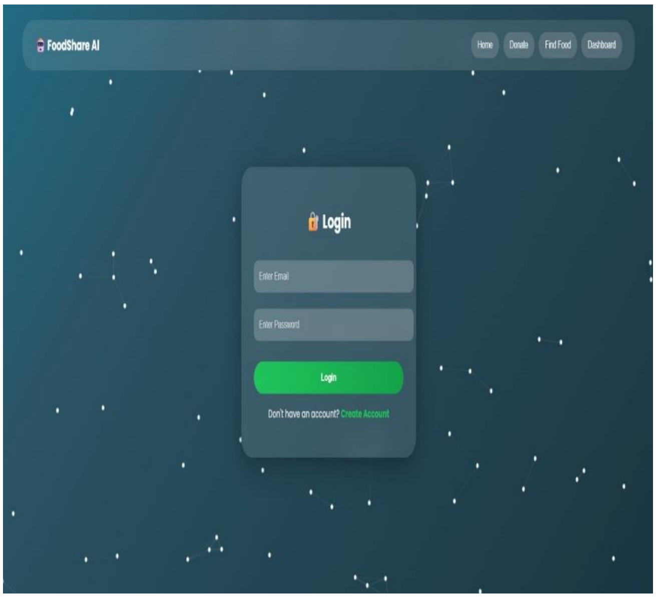


Figure 1: Login and Register page

The login and signup page acts as the entry point of the system, enabling users to securely register and access the platform. New users can create an account by providing basic details such as name, email, and password, while existing users can log in using their registered credentials.

This module also supports proper session management, allowing users to maintain their login state during usage. By providing personalized access, the system enables users to manage their activities such as posting food, viewing available listings, and tracking their interactions. Overall, the login and signup functionality enhances security, user management, and a smooth user experience within the platform.

User Dashboard

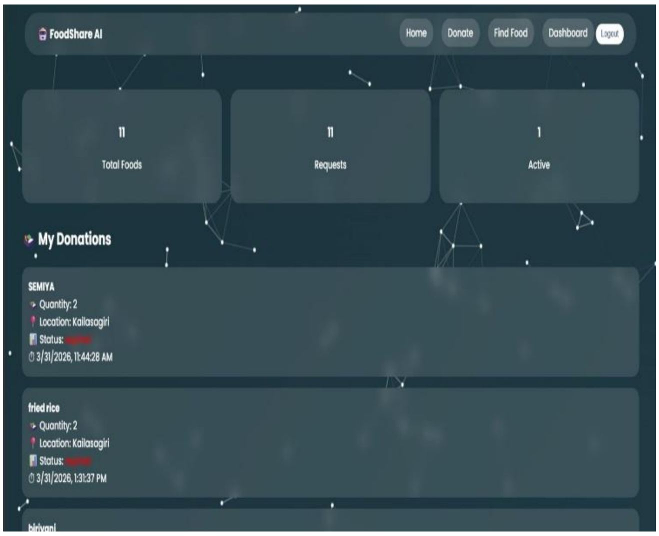


Figure 2: User Dashboard

The dashboard provides an overview of user activities, including posted food, available listings, and notifications. It acts as a central interface for managing all user operations in the system

Post Food Module

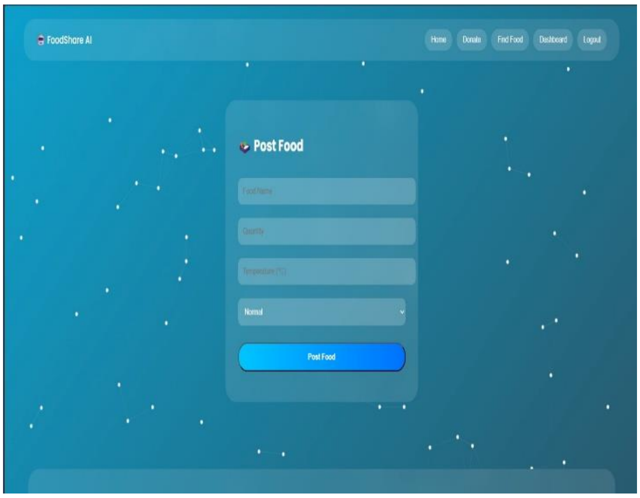


Figure 3: Food Posting Interface

This module allows donors to upload details of surplus food such as food type, quantity, and expiry time. It enables quick and easy submission of food listings into the system.

Post Food with Current Location

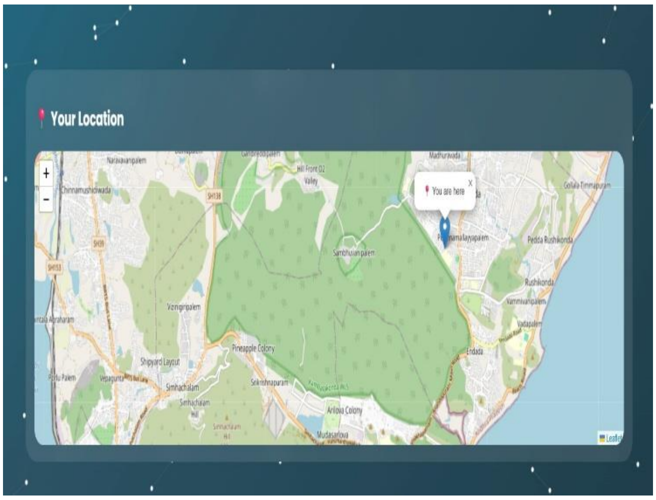


Figure 4: Location-Based Food Posting

The system automatically captures the user's current location while posting food. This helps in identifying nearby recipients and improves the efficiency of food distribution.

Find Food Module

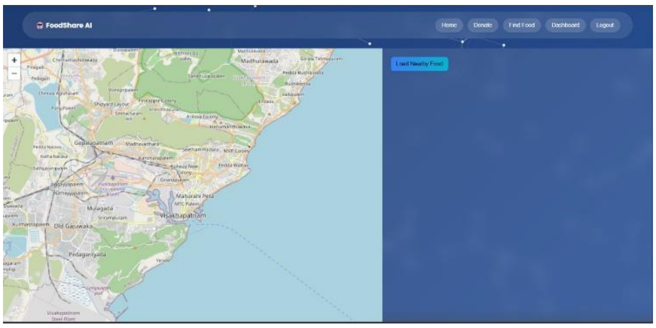


Figure 5: Food Search Interface

Users can search for available food based on location and availability. The system displays filtered and prioritized food listings, helping users quickly find nearby food.

Public Display Food Sharing

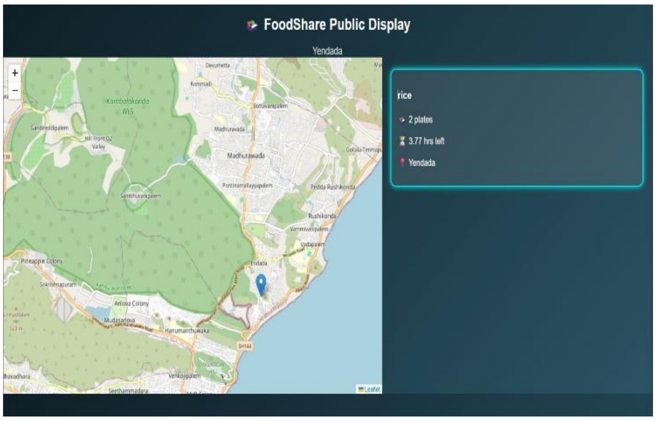


Figure 6: Public Display Unit Interface

The public display unit shows available food listings in common areas. This feature ensures accessibility for users without smartphones, making the system inclusive and practical.

The user interface modules demonstrate that the system is user-friendly, accessible, and efficient. Features like location-based posting, real-time food search, and public display integration improve usability and ensure that surplus food reaches the right people quickly. The system successfully combines technology with accessibility to address food waste and hunger.

6. Conclusion

The proposed system presents an effective and intelligent solution to address the dual challenges of food waste and hunger. By integrating machine learning techniques such as Logistic Regression and Random Forest with a rule-based expiry model, the system ensures reliable spam detection, efficient food prioritization, and accurate freshness evaluation. Unlike existing platforms like OLIO, the inclusion of public display units improves accessibility for users without smartphones, making the system more inclusive.

The results demonstrate that the system achieves high accuracy, good generalization, and practical usability. The combination of data-driven models and simple rule-based logic enhances both performance and interpretability. Additionally, the user-friendly interface modules enable smooth interaction between donors and recipients, ensuring timely and safe food distribution.

Overall, the system provides a scalable, reliable, and socially impactful approach to reducing food waste and supporting people in need. It has strong potential for real-world implementation by NGOs, government organizations, and communities, contributing to a more sustainable and efficient food distribution system.

7. Future Enhancements

The proposed system can be further enhanced by expanding its scope beyond food donation to include other essential items such as clothes, medicines, books, and daily necessities. This will transform the platform into a complete community donation system, helping a larger number of people in need.

In future, the system can support real-time notifications and alerts to inform users about newly available items nearby. Integration of GPS-based tracking can help users easily locate donation points and improve accessibility. Additionally, implementing a rating and feedback system will increase trust and transparency among users.

Advanced features like AI-based image verification can be used to identify and validate donated items, while IoT-based monitoring can be applied for sensitive items like medicines. The platform can also collaborate with NGOs, government bodies, and local communities to enable large-scale donation management.

Moreover, adding multilingual support and offline/SMS-based access will make the system more inclusive, especially for users in rural and underdeveloped areas.

Overall, these enhancements will expand the system from a food-sharing platform to a comprehensive and scalable donation ecosystem, increasing its social impact and usability.

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