International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

An Efficient IoT-Based Automated Food Waste Management System with Food Spoilage Detection

Bhushankumar P. Nemade[1]*, Kamal Shah[2], Bijith Marakarkandy[3], Ketan Shah[4], Bhisaji C. Surve[5], Raminder Kaur Nagra[6]

Submitted: 20/09/2023 **Revised**: 25/10/2023 **Accepted**: 11/11/2023

Abstract: Recent years have seen a growing concern about food waste, leading to advanced research efforts aimed at addressing its widespread consequences. This concern poses a significant threat to the long-term stability of food supply chains, demand patterns, and production processes. Given the universal importance of nutrition, ensuring the quality and safety of food remains a foremost priority. To address this challenge, a groundbreaking food deterioration monitoring system has been developed. This system uses sensors and actuators to monitor gas emissions, humidity, and temperature in fruits and vegetables. It operates with the Node MCU microcontroller, in conjunction with sensors such as the MQ2/MQ4 methane sensor and the DHT11 humidity/temperature sensor. This system provides real-time assessment capabilities for a variety of food items, including rice, bread, samosas, and dal. The system is anchored by a comprehensive dataset that encompasses a diverse range of food items, locations, temperatures, and humidity levels. This dataset forms the foundation for predictive and analytical endeavors. The analytical process encompasses several crucial stages. Rigorous data preprocessing techniques enhance dataset quality by addressing missing values and outliers. The Recursive Feature Elimination (RFE) method optimizes predictive efficiency by iteratively selecting significant features and mitigating overfitting. The M-SMOTE technique corrects class imbalances by generating synthetic samples to balance model training for underrepresented classes. The Random Forest algorithm combines decision trees to offer robust predictive insights. These analyses empower the system to detect spoilage, provide decision-making insights, and predict remaining shelf life, leading to efficient resource allocation. The proposed results demonstrate an accuracy of 94.76%, underscoring its practicality.

Keywords: *IoT, Food spoilage detection, Food Waste Detection, food sustainability, Random Forest, Humidity, M-SMOTE, Recursive Feature Elimination.*

1. Introduction

A shocking 19% of the global population lacks access to food, resulting in malnutrition and premature death, affecting 35% of children under the age of five [1]. Food waste contributes greatly to this dilemma, affecting both hunger rates and the environment. Every year, around 3.1 million children suffer from malnutrition as a result of poor nutrition, emphasizing the importance of the issue [2]. Poor planning, excessive buying, and wasteful food preparation are the chief causes of this waste in settings such as restaurants, hostels, parties, and residences. This wasteful behavior is immoral, as proven by the Food and Agriculture Organization (FAO), which reports that around one-third of all globally produced food is wasted, making this a global concern shown in Figure 1[3].

[1]*Mukesh Patel School of Technology Management & Engineering, NMIMS University, India.*
[2]*Thakur College of Engineering and Technology, Mumbai, India.*
[3]*L. N. Welingkar Institute of Management Development & Research (WeSchool), Mumbai, India,*
[4,5,6] *Mukesh Patel School of Technology Management and Engineering, NMIMS University, India.*

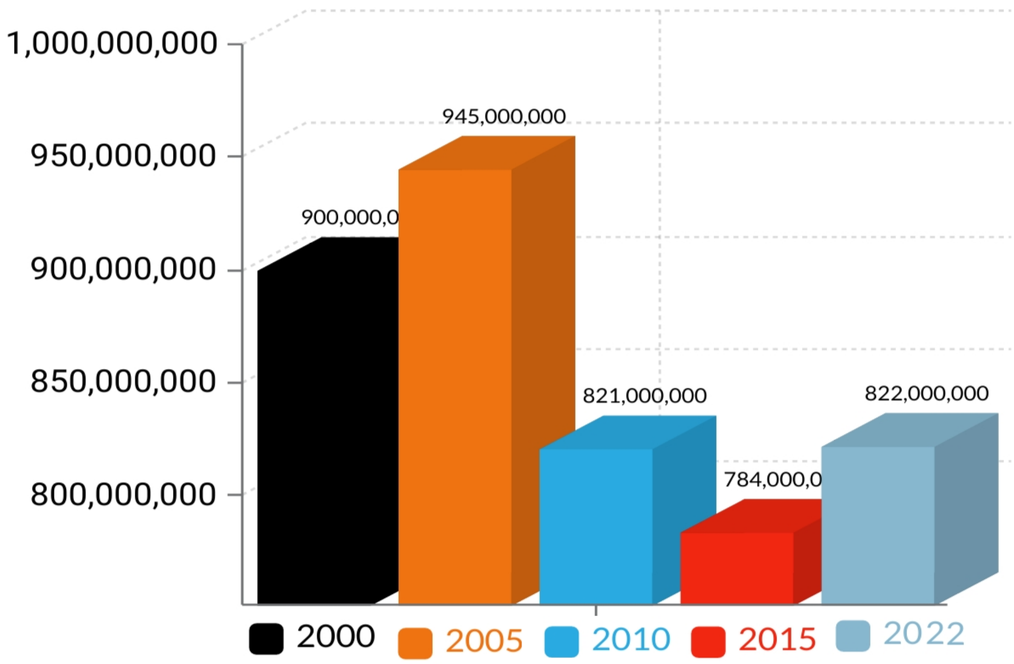

Fig. 1. Global Hunger Statistics

While some attempts have focused on larger-scale food waste, little attention has been paid to the huge amounts of leftover food in households and restaurants. The suggested system serves as a critical platform for redirecting these excess resources to those in need. Individuals who want to provide or receive help from nonprofit organizations can sign up as donors or beneficiaries. Following that, an NGO representative coordinates the collection of extra food from donors and ensures that it is delivered to recipients in accordance with stringent quality criteria [4]. This technical development has enormous promise to address the worrisome trend of excess food going to waste. Furthermore, it provides an opportunity to give to humanitarian causes. In a world suffering from both poverty and food waste, our effort bridges the gap, giving an avenue for charity that addresses both issues at the same time [5]. By embracing this technology, we not only reduce waste but also fulfill a moral commitment to mitigate the devastation caused by hunger and malnutrition. Finally, it shines as a beacon of hope, bringing together noble efforts and practical answers in the pursuit of a better global landscape.

1.1 Need for an Efficient IoT-Based Automated Food Waste Management System With Food Spoilage Detection

The urgent need for the system is due to rising food waste, environmental concerns, and the catastrophic consequences of hunger. This system tries to address these interconnected difficulties by combining technology, data analysis, and continuous monitoring.

a. Growing Food Waste: Food waste has recently become a global concern, with significant volumes of edible foods being discarded throughout the food supply chain. This waste is caused by a variety of circumstances, including overproduction, improper distribution, insufficient storage facilities, and mistreatment. The goal of this system is to drastically reduce food waste by providing a proactive method to monitoring and managing surplus food resources [6].

b. Environmental Impact: Food waste has serious environmental repercussions in addition to impacting human health. The resources used to produce, transport, and prepare the wasted food contribute to unnecessary carbon emissions, deforestation, and water usage. An IoT-based solution that reduces food waste can significantly help to alleviate these environmental constraints [7].

c. Malnutrition and Hunger: Millions of people suffer from malnutrition and hunger, particularly in disadvantaged areas and among children, while food goes to waste. Redirecting excess food to those in need can help reduce humanitarian situations, addressing the moral side of food waste [8].

d. Inefficient Redistribution: Existing solutions frequently focus on large-scale food waste while ignoring smaller-scale contributors such as households, restaurants, and community events. An automated system that connects these sources with charitable groups efficiently can ensure that no edible food is wasted at any level [9].

e. Lack of Monitoring and Accountability: It is difficult to establish where and why food waste occurs without effective monitoring. An IoT-powered system provides real-time data on food spoilage, allowing stakeholders to make informed decisions about how to manage food supplies best [10].

f. Resource Optimization: Inefficient food waste not only harms the environment and nutrition; it also wastes important resources such as land, water, energy, and labor. An IoT-based system can help optimize resource utilization by minimizing waste and reallocating surpluses [11].

g. Shifting Consumer Behavior: By increasing individuals' and businesses' awareness of food waste, this approach promotes a shift toward more responsible consumption and disposal behaviors. Increased awareness can help to cultivate a culture of food stewardship [12].

h. Taking Advantage of Technological Advances: The growing deployment of Internet of Things (IoT) technology provides an unparalleled opportunity to develop new solutions to complex challenges such as food waste. This system provides a scalable and customizable approach to waste reduction by utilizing sensors, data analysis, and automation [13].

Essentially, the proposed system emerges as a comprehensive solution to the multifarious concerns of food waste, environmental degradation, starvation, and inefficiency. It not only solves the underlying issue but also supports a holistic strategy for sustainable food management through real-time monitoring, data-driven insights, and optimized operations.

1.1 Food Spoilage Process

Food spoiling is the degradation of a food item's quality to the point where it is no longer fit for ingestion. External factors such as the food's inherent character, packaging, and processing procedures can all influence its degradation. Food rotting causes the waste of many prepared meals meant for human consumption [14]. This is a significant issue that demands proactive actions to limit needless losses. Consider how quickly fresh apples degrade when exposed to bacteria and the associated gas emissions. An apple can go from being consumable to unusable in a matter of hours. Food deterioration is caused by a variety of microorganisms, including bacteria, viruses, protozoa, and fungi. The consequences of these chemicals can be hazardous to consumers' health [15][16]. Preventive measures, on the other hand, can help alleviate these issues, protecting the nutritional value and overall quality of food products. It is important to highlight that while most germs do not directly cause food poisoning, many foodborne infections are not detectable through smell or taste. Consuming rotten food is therefore strongly advised due to the presence of mycotoxins and microbial metabolites that can cause health hazards. Clostridium perfringens and Bacillus cereus, in particular, can accelerate food spoiling if they penetrate the food item [17]. The food spoiling process is a series of changes that occur over time, eventually rendering a food item unfit for ingestion. This phenomenon occurs as a result of a combination of intrinsic elements inherent in the food and extrinsic factors relating to its surroundings, handling, and storage conditions. External factors like as temperature, humidity, oxygen exposure, and microbial activity all play important roles in hastening the rotting process [18]. Moisture, for example, can provide an environment favorable to the growth of bacteria, molds, and yeasts. These microbes cause enzymatic reactions in the food, resulting in chemical changes that cause unpleasant aromas, tastes, textures, and appearances. The type of food has a considerable impact on the rate and degree of spoiling. Because of their higher water content and nutrient availability for microorganisms, perishable commodities such as fresh fruits, vegetables, dairy products, and meats are more susceptible to quick degradation [19].

Processed and packaged goods, on the other hand, may decay more slowly, but their complicated compositions can also make them susceptible to specific types of spoiling. There are various reason the food spoilage and are represented in figure 2.

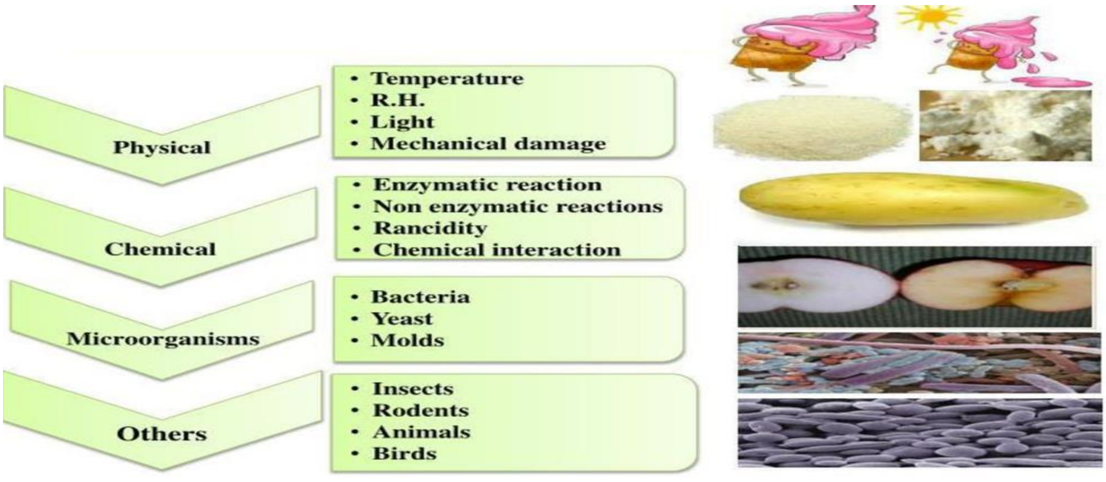

Fig. 2. Food Spoilage Reason

Packaging and processing procedures can either postpone or hasten deterioration. Adequate packing can protect food from external contamination while also preserving its freshness [20]. Inadequate packaging, on the other hand, can hasten deterioration by allowing air, light, or moisture to enter. Microbial agents, which include bacteria, molds, yeasts, and fungi, are the principal causes of food spoilage. These microbes deconstruct the molecular structure of the food, resulting in physical and chemical changes that emerge as visible indicators of rotting. Bacterial activity can cause unpleasant odors, sliminess, discoloration, and gas generation, whereas molds frequently appear as visible growth on the food's surface [21]. Food rotting has effects that go beyond economic losses and environmental impacts to include public health issues. Foodborne infections can develop from the ingestion of damaged food due to the multiplication of hazardous bacteria and the probable creation of toxins.

2. Related Theory

Food waste is a severe global concern, covering the astonishing reality that nearly one-third of the world's food output is lost, resulting in significant economic repercussions owing to poor resource use across the supply chain. This squandering goes beyond monetary losses to become a significant contributor to environmental problems, most notably the release of harmful greenhouse gases like methane and the depletion of precious natural resources. Concurrently, the preservation of optimal food quality is a top priority, fraught with complexities arising from the intricate processes involved in food production, handling, and distribution. Despite its indisputable importance, constantly monitoring and maintaining food quality is a time-consuming and difficult job. As a result, there is an urgent need to develop a comprehensive and effective system tailored to address this multifaceted challenge of food waste, integrating cutting-edge technologies for real-time monitoring, refining supply chain operations to minimize waste, empowering consumers through education, and enacting supportive policy frameworks, collectively fostering a sustainable food ecosystem that resonates with both present and future needs [22].

Ahmed M. et al. [23] presented the importance of real-time monitoring and control in maintaining food quality and minimizing business losses. They emphasize the growing use of Internet of Things (IoT) principles to prevent food spoilage caused by varying storage conditions. Sensor data analysis provides predictive insights and identifies spoilage factors. Their novel approach combines Adaptive Random Forest prediction and IoT to automate control mechanisms, regulating environmental factors known to affect food quality such as temperature and humidity. Sensor data storage in the cloud enables proactive analyses, reducing spoilage risks. The Random Forest Optimizer technique forecasts food freshness accurately and actively addresses deviations. With an accuracy rate of 89.32%, this study contributes to technology-driven food preservation strategies that are in line with sustainable resource management.

Sowmya J. et al. [24] presented a system based on the OpenCV Python library and Convolutional Neural Network (CNN) technology. This method seeks to identify and assess the quality of food items. Using this technology, tasks such as recognizing fruit types and evaluating their quality are completed through reliable and exact data analysis. To successfully sort the fruits with precision, the proposed setup includes crucial components such as a microcontroller, instruments, a camera, and a conveyor belt layout. This methodical approach assures precise and efficient fruit separation. Additionally, the system has sensors to monitor storage conditions actively, and this real-time data is transferred to the cloud using Internet of Things (IoT) technology. This seamless communication aids in the preservation of the fruit's freshness over extended periods of time, which is critical for businesses aiming to supply fresh and delicious items to their customers. Essentially, the strategic use of computer vision and cutting-edge technologies enables food processing firms to provide top-tier products to consumers in a cost-effective and simplified manner.

G. Sharada et al. [25] presented a system embracing sophisticated technologies and Internet of Things (IoT) principles, utilizing Arduino as well as script programming and a variety of sensors such as DHT sensor, moisture sensor, MQ3 Sensor, and Arduino UNO. In this work, a unique method for analyzing and identifying food quality is developed. To ease this process, the sensors are integrated with Arduino. While refrigerators are important for food preservation because they slow bacterial growth, there may be times when food products meant for long-term storage are mistakenly overlooked. The purpose of this study is to address the problem of food rotting by using sensors to continuously monitor food items. When the sensors detect old food, they send signals indicating freshness and quality, alerting the user via a registered mobile phone.

Shazmina G. et al. [26] introduced an innovative approach using affordable sensors and the Arduino UNO microcontroller. Their eNose system, which includes MQ4 and MQ135 sensors, detects gas emissions from various food items. The study involves data collection from different foods, with the MQ4 sensor identifying CH_4 gas and the MQ135 sensor detecting CO_2 and NH_3 gases. A weight sensor utilizing a 5 kg strain gauge load cell and HX711 A/D converter is integrated to measure food wastage. Following calibration, a machine learning algorithm employing a decision tree model predicts food items based on gas emissions, achieving a system accuracy of 92.65%. This technology-driven system contributes to reducing food wastage at homes and restaurants, providing daily reports for enhanced waste management.

Pooja S. et al. [27] presented a study with meat as the primary objective for non-destructive, convenient, and speedy evaluation of freshness at home and on the road. The food sector is important in today's economy, but it faces a big challenge: food deterioration, particularly with regard to meat, fruits, and vegetables. Detecting ruined commodities is critical since undetected spoiling might pose health risks to consumers. Currently, manual inspection along conveyor belts is used to assess the quality of fruits and vegetables. Automated techniques could improve spoiling detection accuracy while reducing the requirement for manual intervention. Contaminated and damaged food poses health risks and leads to foodborne illnesses, which impact a large number of people every year. The main problem is the time-consuming manual testing of temperature-sensitive food items, which can be streamlined with continuous wireless monitoring, saving time and resources. While temperature and quality monitoring are used in transit and distribution, this study suggests a more precise, continual quality assessment of items made possible by centralized data gathering and analytics. Such approaches have the ability to reduce food waste drastically, improve transportation efficiency, and quickly remove tainted or rotten food from the supply chain, so addressing the problem of food spoilage through improved monitoring and sensing.

Peerzada S. et al. [28] conducted research on tracking food waste and providing incentives to users. The study entails showing real-time individual food waste statistics on screens as well as a website for future reference. The primary focus of this study is the comprehensive tracking of food waste among individuals. Our proposed solution not only tackles this worry but also produces parallel results, sending detailed information on the amount of extra food to both administrators and users each time.

Tamris P. et al. [29] developed a system for continuous monitoring of food loss and waste (FLW), a critical undertaking for improving food security and mitigating the effects of climate change. These technical solutions permit the continuing monitoring of food quality by utilizing real-time sensors assessing quality parameters such as temperature and humidity, hence contributing in the reduction of FLW. Despite a wealth of literature on sensor technologies, there is still a gap in understanding the breadth, use, and extent of these sensors in monitoring FLW. To address this, a comprehensive analysis of 59 published research concentrating on sensor technologies for minimizing food waste across food supply chains was conducted, with the insights and lessons learned amalgamated. The review focuses on two major aspects: the IoT technologies used and the supply chain characteristics in which these technologies have been integrated. It looks into supply chain variables such as product kind, supply chain stage, and geographical region, as well as sensor technology dimensions such as monitored parameters, communication protocols, data storage, and application layers. According to the findings, while monitoring fruits and vegetables using temperature and humidity sensors to address their high perishability and short shelf lives is a repeating research focus, several other uses and technologies are being investigated to reduce food waste. Furthermore, the study emphasizes the enormous potential in this domain, pushing for ongoing discovery and deployment of IoT technologies to improve food production, management, transportation, and storage, ultimately advancing the cause of FLW reduction.

3. The Proposed Methodology

The proposed method attempts to create an efficient solution for expediting the food donation process by connecting donors with NGOs. The system has a number of elements to facilitate interactions between funders and non-governmental organizations. The use of machine learning-based methods are used to determine the closest possibilities for food gathering is an important component of this system. The proposed solution speeds up the relationship between donors and NGOs by taking into account aspects such as location, quantity, and food varieties to provide relevant options. The method makes use of an Internet of Things (IoT)-based electronic device to improve the efficiency of food gathering. NGO staff use this equipment to assess the quality of donated food and prevent the distribution of spoiled foods. It continuously monitors temperature and other factors that influence food rotting and alerts NGO employees in real-time. The successful deployment of this system involves collaboration among donors, non-governmental organizations, and system administrators. Donors give precise information regarding food type and location, while NGOs monitor food quality. The suggested method has the potential to significantly improve food donation operations, reduce waste, and assure the safe delivery of healthy food to people in need.

Approach: Our suggested system aims to simplify food donation procedures by allowing donors to update their food information and location easily. This enables NGOs to locate the closest donor and receive food immediately. To accomplish this, we use the powerful Google Maps API to handle donor locations and routes. This allows

NGOs to organize collecting routes more efficiently, saving travel time and increasing efficiency. In addition, our approach employs a novel incentivization method to incentivize food giving. This approach pays donors depending on the quality and amount of food they donate, encouraging recurring contributions of high-quality, healthy foods. Overall, our suggested system provides a user-friendly platform for food donation while maximizing efficiency through the use of modern technologies.

The Internet of Things device, which includes DHT11 and MQ2 sensors, continuously measures temperature, humidity, and methane gas levels to determine food spoilage. This provides an additional degree of security and quality assurance to the donation process. An NGO food collector proceeds within a predetermined time range after the IoT system approves food for collecting. The system determines this timeframe based on projected deterioration rates, ensuring that collected food remains fresh and safe. Our suggested solution uses IoT technology to prevent food waste by ensuring that only fresh and consumable foods reach NGOs. This not only maintains food quality but also lowers the danger of foodborne illness, resulting in a safer and more trustworthy food donation process. Our approach, when integrated with IoT technology, has the potential to transform food donation procedures by delivering a more efficient, secure, and effective platform. The working of proposed architecture as described in figure 3 is discussed below.

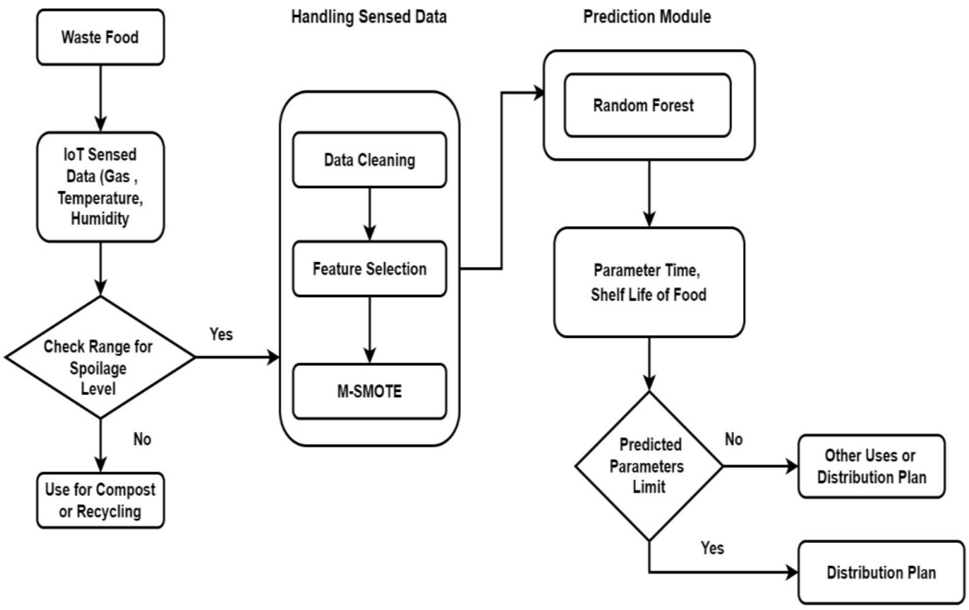

Fig. 3. The proposed system architecture

The MQ2 sensor, DHT11 sensor, and ESP 8266 Wi-Fi module are initially interconnected with the Wi-Fi module, followed by programming using the Arduino IDE to extract the appropriate system output. Following that, the system is linked to an online portal, which provides the necessary data. This webpage is designed to generate precise insights on food spoilage and is built with HTML, CSS, and JavaScript, as well as frameworks such as React JS. Through an API, the sensor outputs connect to the portal. Our self-compiled dataset covers diverse food items across distinct locales and environmental variables, including temperature and humidity fluctuations, for reliable forecasts on food rotting. To determine food rotting, the model considers elements such as methane levels, temperature, and humidity. Accurate forecasts can be obtained by training machine learning models to assess spoilage based on oxygen and ammonia levels. This is extremely useful for food producers and retailers attempting to assure product safety.

We incorporate IoT technology to ensure the quality of gathered food, expanding the breadth of our food donation online service in an innovative way. The Internet of Things device, which includes DHT11 and MQ2 sensors, continuously measures temperature, humidity, and methane gas emissions to determine food spoilage. This additional layer of security and quality assurance strengthens the food donation procedure. Following the clearance of the IoT system, an NGO food collector continues to retrieve the donation within a predetermined time range. The system determines this time range while accounting for the expected loss rate, ensuring the freshness and safety of the collected food. Our goal with the incorporation of IoT technology is to reduce food waste by guaranteeing that only fresh and consumable food reaches NGOs. This dual function protects food quality while also lowering the risk of foodborne infections, resulting in a more secure and dependable food donation process. Our online application combined with IoT technology has the potential to transform food donation practices by providing a platform that is more efficient, secure, and effective for food distribution.

Data Collection: The use of Internet of Things (IoT) sensors is used for the initial data collection. The equation 1 represents the mathematical representation of the acquired data:

$$S\_D=\{S\_1,S\_2,S\_3,....................,S\_N\} \quad (1)$$

S_D represents the dataset, and S_N refers to sensor data instances numbered from 1 to N.

Data Cleaning: Parameters such as methane gas emissions, temperature, and humidity were thoroughly cleaned. The data obtained from sensors that detect these critical parameters, including timestamps, food specifics, and position information, was meticulously structured. When some observations were absent, procedures like estimating methane gas emissions and filling in temperature and humidity gaps were used. Unusual data points, such as excessively high or low values, were identified and, if necessary, validated or corrected. To ensure uniformity, the units used to quantify methane gas emissions, temperature, and humidity were standardized, and any categorical data was translated into numerical values suitable for modeling. These efforts ensured the dataset's accuracy and utility, allowing for the creation of effective solutions for minimizing food waste and detecting possible spoilage. This method drew on data from methane gas emissions, temperature fluctuations, and humidity levels.

Recursive Feature Elimination (RFE): It is an effective feature selection technique that may be used for both regression and classification issues. It works by iteratively deleting less significant characteristics based on relevance scores supplied by a machine learning method of choice, such as Linear Regression or Random Forest. In a regression setting, RFE refines the model by preserving the most influential features for predicting numerical outcomes, but in classification tasks, it picks the features that best distinguish between various classes. RFE improves model accuracy, decreases overfitting, and speeds decision-making by systematically removing less relevant characteristics, making it an efficient technique for optimizing predictions in the dataset, whether for quantifying spoiling degree or recognizing spoilage status.

The suggested system investigates several strategies for dealing with imbalanced datasets. This is significant since simply looking at accuracy is insufficient. Other metrics, like as precision, recall, F1-Score, Kappa, and ROC curves, are used to assess how effectively the system operates.

We employ either under-sampling or over-sampling approaches to deal with the problem of imbalanced datasets. We add new records (rows) from the minority classes to the training dataset using various attributes in the over-sampling procedure. We eliminate certain records (rows) from the majority class using the under-sampling technique. The M-SMOTE method [30] is used to address the class imbalanced problem.

M-SMOTE Method

It is a hard challenge to select instances from the minority class, select sample attributes and types, determine the sampling rate, and figure out how to distribute samples within the minority class. To identify the optimal solution, we need to use mathematical modeling. SMOTE, a popular strategy for generating fresh samples for minority classes, has drawbacks. It disregards close samples and may result in increased class overlap and noisy data. SMOTE also suffers with high-dimensional data and creates duplicate samples for minority classes, both of which have an impact on model correctness.

To address this, we provide M-SMOTE, a novel technique. M-SMOTE performs non-overlapping oversampling for minority classes. It accepts two parameters: the Dataset and Dy (the name of the dependent variable). The initial stage in M-SMOTE is to identify and correct outliers. To find and remove outliers, we utilize the RemoveOutlier function, which use the Z-score approach. For this procedure, Equations 2, 3, 4, 5, and 6 are used. Using equation 9, we divide the dataset into dependent (Dy) and independent (Dx) variables, which are then returned to the M-SMOTE function.

Remove Outliers (RemoveOutlier) Algorithm:

The goal of this function is to remove outliers from the dataset using the Z-score method. Dataset with specified ranges or limitations for each attribute as input. Dataset with less noise and outliers as an output. Iterate over each column (col) in the dataset given Dataset (D):

Algorithm

$D \leftarrow Dataset$
for col in $dataset.columns$ **do**
  $z \leftarrow \frac{x-\mu}{\sigma}$ ▷ Calculate z-score (Equation 2)
  $\mu \leftarrow \frac{\sum_{i=1}^{n} col[i]}{length(col)}$ ▷ Calculate mean (Equation 3)
  $\sigma \leftarrow \sqrt{\frac{\sum_{i=1}^{n}(col[i]-\mu)^2}{length(col)}}$ ▷ Calculate standard deviation (Equation 4)
  $UBx \leftarrow \mu + z \cdot \sigma$ ▷ Calculate Upper Boundary (Equation 5)
  $LBx \leftarrow \mu - z \cdot \sigma$ ▷ Calculate Lower Boundary (Equation 6)
  $OV \leftarrow dataset[(D(col[i]) > UBx)OR(D(col[i]) < LBx)]$ ▷ Find Outliers (Equation 7)
  $ND \leftarrow D[(D(col[i]) < UBx)AND(D(col[i]) > LBx)]$ ▷ Remove Outliers and Create New Dataset (Equation 8)
  $Dx, Dy \leftarrow split(ND)$ ▷ Split New Dataset (Equation 9)
return Dx, Dy

Algorithm M-SMOTE(dataset, Dy):

Problem description: To perform the oversampling for minority classes without class overlapping

Input: Dataset with dependent features Dx and independent features Dy.

Output: To generate the synthetic samples for minority classes without class overlapping.

Algorithm :

$Dx, Dy \leftarrow RemoveOutlier(dataset, Dy)$ ▷ Remove outliers
$CMJ \leftarrow \max(Count(Dy))$ ▷ Equation (10)
$CMN \leftarrow CN - CMJ$ ▷ Equation (11)
$M \leftarrow length(CMN)$ ▷ Equation (12)
$J \leftarrow 0$
while $J < M$ **do** ▷ Loop while J ¡ M
  $ratio \leftarrow \frac{count(CMN[J])}{count(MJ)}$ ▷ Equation (13)
  if $ratio < 0.8$ **then**
    $G \leftarrow (count(MJ) - count(CMN[J])) \cdot \beta$ ▷ Equation (14)
    for $i = 1$ to G **do**
      Generate new synthetic sample S_i:
      $S_i \leftarrow X_i + (XZ_i - X_i) \cdot \lambda$ ▷ Equation (15)
      Where $\lambda = random(0, 1)$
    for $i = 1$ to G **do**
      Add newly generated sample to dataset:
      $Dataset \leftarrow S_i$ ▷ Equation (16)
      $J \leftarrow J + 1$

Using equation 10, we determine the length of the majority class (CMJ denotes the majority class). Equation 11 is used to compute the minority class list, which is then assigned to CMN. Equation 12 is used to obtain the total number of minority classes (M). We utilize equation 13 to get the minority-majority class ratio. If the ratio is less than 0.8, the class is considered unbalanced. We determine the total number of synthetic samples (G) to be generated for minority classes using equation 14. After that, Equation 15 is used to generate G samples and add them to the dataset. This approach generates a new dataset free of outliers, resulting in a clean dataset for producing synthetic samples for minority classes. To select the best algorithm, metrics such as precision, recall, accuracy, and execution time are used. In order to get better prediction results, the proposed approach leverages the Random Forest algorithm within the prediction module.

Enhanced Random Forest with Outlier Detection Mitigation Algorithm

The Enhanced Random Forest with Outlier Detection Mitigation Algorithm is a sophisticated machine learning technique that combines the power of the Random Forest algorithm with novel techniques for mitigating the impact of outliers on model performance. This algorithm tackles the issue of outliers, which are data points that deviate significantly from the majority of the dataset and can have a negative impact on the accuracy and robustness of traditional machine learning models. The algorithm starts by constructing an ensemble of decision trees using the Random Forest framework. Each decision tree is trained on a different subset of the data, and its predictions are combined to yield a final prediction. This ensemble approach improves the model's accuracy, generalizability, and resistance to excessive overfitting. This algorithm distinguishes itself by incorporating outlier detection and mitigation techniques within the Random Forest structure. It identifies and addresses outliers during both the training and prediction phases, resulting in improved model performance in the presence of outlier-rich datasets.

The following are the algorithm's key components:

Outlier Detection: The algorithm employs advanced outlier detection methods to identify potential outliers in the training data. This step ensures that the model is aware of any potential anomalies that may interfere with its learning process.

Mitigation Strategies: Once outliers are identified, the algorithm employs novel strategies to mitigate their impact on the model's learning process. This could include reducing the impact of outliers during the tree-building process or reassigning them to appropriate data clusters.

Ensemble Learning: The algorithm creates an ensemble of decision trees that collaborate to make predictions. The algorithm improves predictive accuracy and lowers the risk of overfitting by combining the outputs of multiple trees.

Robust Predictions: During the prediction phase, the algorithm uses the collective intelligence of the ensemble to make robust predictions. Outliers that were detected during training are treated appropriately during this phase, improving the model's ability to handle new, unknown data.

The "Enhanced Random Forest with Outlier Detection Mitigation Algorithm" is a efficient machine learning technique that combines the power of the Random Forest algorithm with novel techniques for mitigating the impact of outliers on model performance. This algorithm tackles the issue of outliers, which are data points that deviate significantly from the majority of the dataset and can have a negative impact on the accuracy and robustness of traditional machine learning models.The algorithm starts by constructing an ensemble of decision trees using the Random Forest framework. Each decision tree is trained on a different subset of the data, and its predictions are combined to yield a final prediction. This ensemble approach improves the model's accuracy, generalizability, and resistance to excessive overfitting. This algorithm provides several requiring benefits. The algorithm adeptly navigates datasets riddled with noise and outliers, yielding increased robustness and predictions that inspire confidence by seamlessly integrating cutting-edge outlier detection and mitigation techniques. Using the power of ensemble learning, it creates predictions that are resistant to individual outliers, thereby increasing the overall predictive efficacy. The algorithm's ability to extrapolate insights to novel, previously unseen data domains is a remarkable feat, culminating in a truly versatile application spectrum. Furthermore, the algorithm's tailored treatment of outliers highlights a tangible reduction in bias resulting from extreme data points, resulting in predictions that are fair and equitably distributed. As a result, the algorithm represents a paradigm-shifting approach to dealing with machine learning outliers. It constructs a fortified, refined, and adaptable model by seamlessly combining the strengths of ensemble learning, innovative outlier detection, and mitigation strategies.

Algorithm Enhanced Random Forest with Outlier Detection and Mitigation

Input: Dataset X, Target labels y
for col in X columns **do**
    Calculate z, μ, σ, UBx, and LBx using provided equations
    Calculate $Outliers$ using equation $Outliers \leftarrow dataset[(D(col[i]) > UBx)OR(D(col[i]) < LBx)]$
    $X_{new} \leftarrow X$ excluding samples in $Outliers$
    $y_{new} \leftarrow y$ excluding corresponding labels
Initialize empty list $forests$
for $tree\_id = 1$ to num_trees **do**
    $samples, labels \leftarrow RandomSample(X_{new}, y_{new})$
    $tree \leftarrow TrainDecisionTree(samples, labels)$
    Append $tree$ to $forests$
Output: List of trained decision trees $forests$

The model is trained to improve prediction accuracy for a certain input sample, resulting in accurate outputs. In a larger sense, the circuit layout and successful interaction among the components were critical in allowing the IoT device's ability to monitor food freshness and identify spoiling based on sensor data. Microorganisms have varied temperature preferences, which have a substantial impact on food safety. Some microbes thrive in frigid surroundings, whereas others flourish in room temperature or higher temperatures. Recognizing these variations is critical for maintaining food safety. Defining temperature settings acceptable for hazardous bacteria is critical for selecting the appropriate storage temperature, limiting their reproduction potential, and ensuring food safety. This strategic approach to food donation adds an extra degree of security and quality assurance to the process. After the IoT system validates that the food is suitable for pickup, an NGO representative will recover the item within a predetermined timeframe. The system determines this timeframe by taking into account the expected spoiling rate, ensuring that the gathered food remains fresh and safe to ingest.

Our goal with the integration of IoT technology is to reduce food waste by ensuring that only fresh and consumable food is donated to NGOs. This not only maintains food quality but also reduces the risk of foodborne illness, increasing the dependability and safety of the food donation process. Finally, this application creates a simple and efficient platform for food donation, leveraging cutting-edge technology to improve the efficiency and effectiveness of the process. The software smoothly integrates Google Maps API for optimum collecting routes, introduces a unique incentive system to encourage high-quality and nutritional donations, and makes use of IoT technologies to ensure the freshness and compatibility of donated food. We hope to reinvent the approach to food contributions by combining these technology features, providing a more efficient, secure, and impactful platform for the food donation attempt.

4. Result and Discussion

Data was collected for each specific item after a series of tests were performed on various food varieties using the IoT gadget. This dataset was used to calculate threshold values for the observed parameters, which included methane levels, temperature, and humidity. These threshold levels served as criteria for identifying when food had spoiled and was no longer fit for ingestion. The temperature fluctuation documented for each food item was an important revelation from the testing, which was ascribed to numerous external variables within the surrounding environment. Because of this unpredictability, temperature alone may not reliably signal food deterioration and may be influenced by external factors such as weather changes or other environmental factors.

Despite this variation, the testing using the IoT device was very adept at detecting rotting in the examined food items. The device demonstrated its ability to provide precise results by monitoring methane levels, temperature, and humidity. These IoT devices may collect information on food storage conditions, monitor food waste, and improve food inventory management, resulting in financial savings for businesses and reducing the environmental impact of food waste. However, employing a food waste management system integrated with an IoT device to gauge methane gas levels and temperature in the food storage vicinity emerges as an effective strategy, ensuring the provision of fresh and safe food to consumers, reducing the risk of foodborne illnesses and preventing food waste.

The food waste management system includes an IoT device that monitors the methane gas level and temperature in the food storage space. In general, if the methane gas level exceeds 400 and the temperature exceeds 40 degrees, the food is considered rotten. This system ensures that only fresh and safe food is delivered to consumers, reducing the risk of foodborne illness and food waste. An experimental examination was carried out to assess the system's precision and usefulness in identifying food rotting. The study concentrated on commonly consumed foods such as samosas, rice, and lentil soup. The study of the following parameters was used to determine food spoilage: 1. Methane gas level 2. Humidity 3. Temperature

Table 1, Table 2, and Table 3 provide a complete summary of the freshness status predictions for various food items based on particular characteristics. Methane gas level, humidity, and temperature are among the characteristics examined. The output of the forecast indicates the state of the food at various time periods. The initial condition of the food products, namely Samosa, Lentil Soup, and Cooked Rice, is evaluated under the "Status of Fresh Food" area. Methane Gas, Humidity, and Temperature data are related to each food type. The "Prediction" column displays that the condition of all three food products is good at the provided measurements. The "Status of Food After 12 Hours" section depicts the changes in metrics after monitoring the food for 12 hours. The values for Methane Gas, Humidity, and Temperature for Samosa, Lentil Soup, and Cooked Rice have changed. While Samosa and Cooked Rice remain in fair condition, Lentil Soup is beginning to spoil, as suggested by the "Prediction."

The final status of the food products is assessed in the "Status of Food on Spoiled" segment. The amounts of Methane Gas, Humidity, and Temperature have all changed, resulting in noticeable alterations. At this point, all three food items – Samosa, Lentil Soup, and Cooked Rice – are labeled "Spoiled." The table shows how the prediction results change over time based on key characteristics, revealing light on the transition from "Good" to "Spoiled" circumstances for various food categories.

Table 1: Food Spoilage Detection in Condition 1

Status of Fresh Food				
Parameters/ Food Type	**Methane Gas**	**Humidity**	**Temperature**	**Prediction**
Samosa	317	39	27.12	Food condition is Good
Lentil Soup	416	58	29.65	Food condition is Good
Cooked Rice	343	59	29.54	Food condition is Good

Table 2: Food Spoilage Detection in Condition 2

Status of Food after 12 Hours				
Parameters/ Food Type	**Methane Gas**	**Humidity**	**Temperature**	**Prediction**
Samosa	438	57	28.42	Food condition is Good
Lentil Soup	479	69	30.19	Food Spoilage Started
Coocked Rice	368	47	30.12	Food condition is Good

Table 3: Food Spoilage Detection in Condition 3

Status of Food on spoiled				
Parameters/ Food Type	**Methane Gas**	**Humidity**	**Temperature**	**Prediction**
Samosa	589	64	30.12	Food is Spoiled
Lentil Soup	489	79	32.89	Food is Spoiled
Coocked Rice	390	39	28.9	Food is Spoiled

The proposed system has performed Multi-Parameter Food Condition Analysis using figure 4.

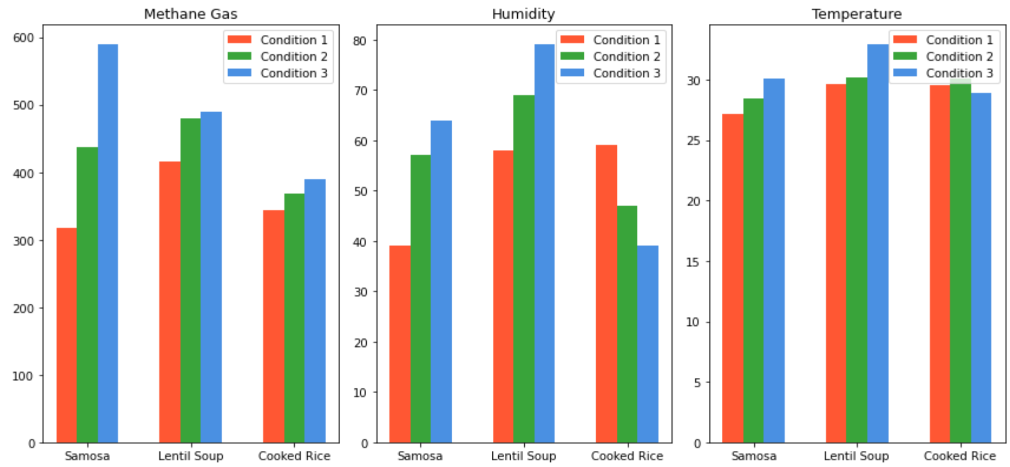

Fig. 4. Multi-Parameter Food Condition Analysis

The investigation entailed using IoT devices to conduct testing on various food items at different time intervals. Samosas were tested after 18 hours, rice after 36 hours, and dal after 12 hours of cooking. Temperature, humidity, and methane gas were among the variables studied. Analyzing the collected data revealed that the IoT gadget indicated food spoiling, a conclusion supported by the existence of a blinking blue light. For a comprehensive comparison, the Random Forest algorithm was applied in two scenarios: one with MSMOTE (Minority Synthetic Over-sampling Technique) and another without MSMOTE. The results are presented in the Table 4.

Table 4: Comparison Table: Random Forest Results with and without MSMOTE

Scenario	Accuracy	Precision	Recall	F1-Score
Without MSMOTE	0.85	0.87	0.83	0.85
With MSMOTE	0.94	0.91	0.94	0.92

The performance analysis of the proposed system is graphically represented using figure 5.

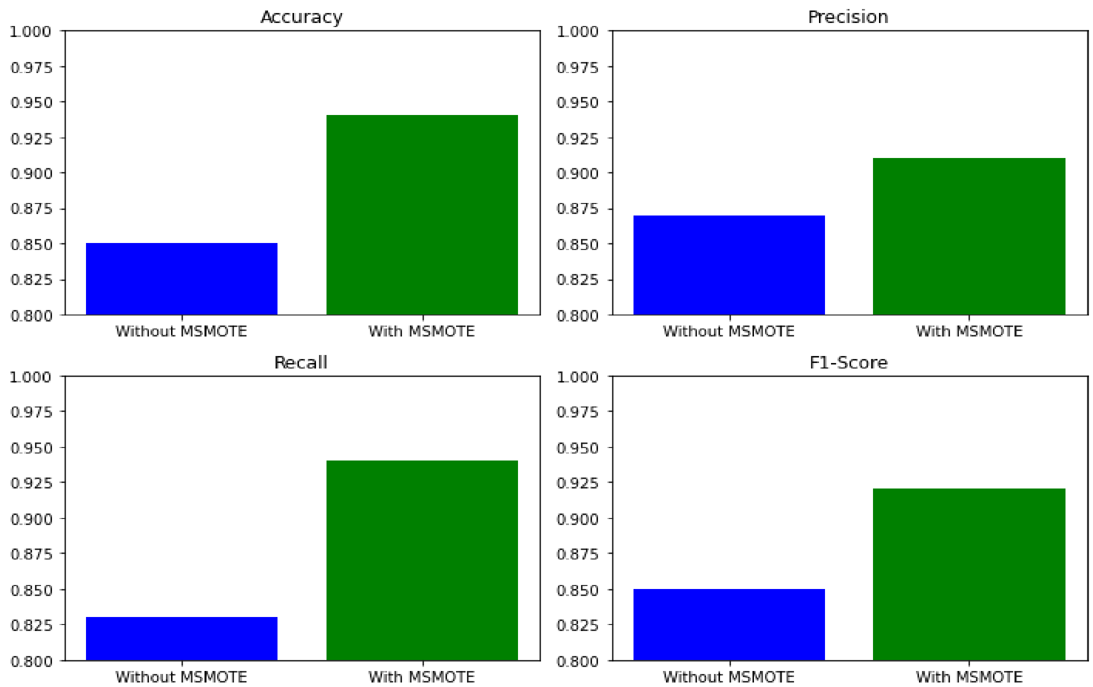

Fig. 5. The performance of proposed system with and without M-SMOTE

In the comparison table, the scenario with MSMOTE demonstrates improved accuracy, precision, recall, and F1-score. Employing a food waste management system integrated with an IoT device for monitoring methane gas levels and temperature in food storage spaces proves to be an effective strategy. It ensures the provision of fresh and safe food, reduces the risk of foodborne illnesses, and mitigates food waste, benefiting both businesses and the environment.

Furthermore, we conduct a comparative analysis between the outcomes of our proposed method and those of a previous system, taking into account performance metrics such as accuracy and ROC scores.

Our proposed method was thoroughly tested using a diverse set of 3000 sample food datasets, effectively demonstrating its capabilities. To ensure unwavering consistency and reliability, all experiments were precisely implemented within a stable computing environment. This environment included the Windows 10 operating system, the Python programming language, and hardware with 16 GB RAM, an i7-4500 CPU, and a 1TB hard disk.

Precise Refinement and Datasets: Our method was customized to perfectly align with the unique characteristics of the datasets and the complexities of parameters, resulting in an optimal configuration that produced insightful results.

Comprehensive Test Outcomes Presentation: The study investigates our method's performance in comparison to previous machine learning models. We provide a thorough explanation of accuracy and Receiver Operating Characteristic (ROC) curve scores for each model, which is concisely summarized in Table 5. This visual compilation expertly captures the achieved results. The "Accuracy Score" column provides a tangible metric of our method's ability to accurately categorize fresh and non-fresh observations, whereas the ROC scores provide a profound measure of each model's capability for differentiation. Our experimental journey reveals subtle differences in model performance that are intricately linked to dataset complexities and the strategic application of balancing techniques.

Table 5: Accuracy and ROC Results for Different Models

Machine Learning Model	**Accuracy (%)**	**ROC Score**
Random Forest [23]	89.32	0.951
Proposed System	94.76	0.915

The Figure 6 and 7 demonstrates the performance measures of two different machine learning models, namely the Random Forest and the Proposed System. The accuracy (%) parameter indicates how well each model categorizes observations. The Random Forest model achieves an accuracy rate of 89.32%, whereas the Proposed System outperforms it significantly with a significantly higher accuracy rate of 94.76%, highlighting its superior classification capability. Furthermore, the Receiver Operating Characteristic (ROC) score for both models is provided, indicating their ability to discriminate between various categories. The Random Forest has a ROC score of 0.951, while the Proposed System has a commendable ROC score of 0.915, implying a competitive ability to distinguish categories despite a slightly lower score.

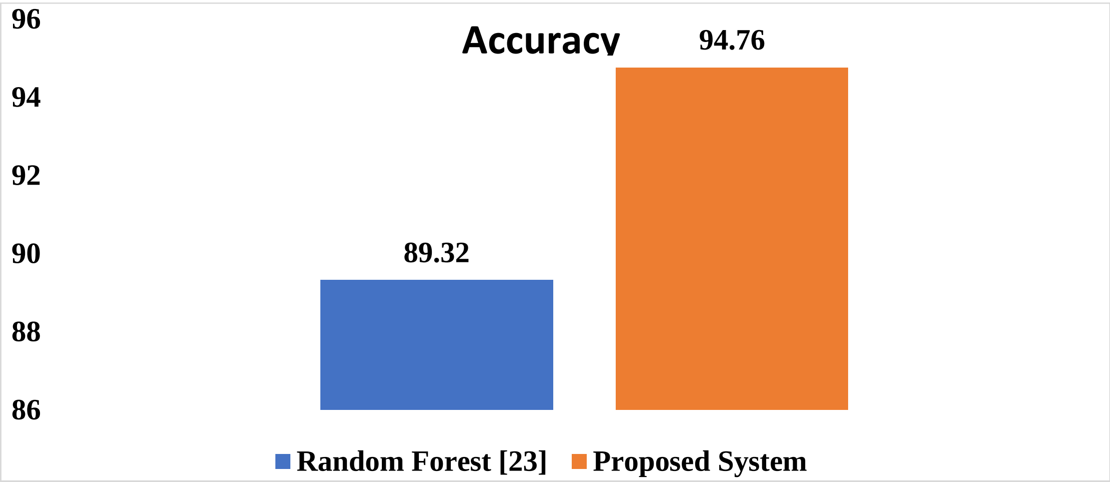

Fig.6. Accuracy of the proposed system vs Random Forest classifier

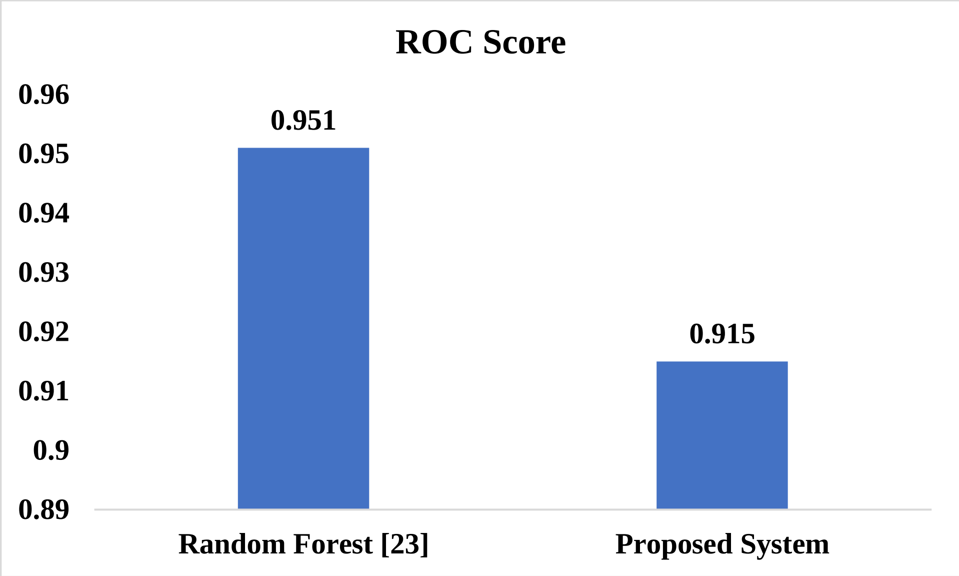

Fig.7. ROC curve of proposed system vs Random Forest classifier

our method was thoroughly tested and proven to be excellent at accurately categorizing food datasets. The results of our detailed comparison show that it's better than other methods and suitable for tasks that need precise and reliable categorization.

5. Conclusion

In conclusion, our research underscores the critical issue of food waste and introduces an impactful solution that combines IoT technology and an intuitive online platform. This comprehensive approach streamlines food donation processes and enhances food management strategies, ultimately contributing to a more sustainable and efficient food ecosystem. Our proposed strategy leverages a user-friendly online platform to facilitate swift food donations, while smart IoT devices optimize the collection efforts. By equipping various groups with these advanced devices, we empower efficient pickups, minimizing the likelihood of donated food going to waste. The successful tests on fresh food items demonstrated impressive accuracy rates, approximately 94.76%, in measuring key parameters such as temperature, humidity, and methane gas levels, ensuring the quality of donated food.

The integration of an innovative incentive mechanism also stands as a cornerstone of our approach. By encouraging a culture of regular and high-quality food donations, we address the root causes of food waste and create a positive feedback loop for sustainable practices. Furthermore, our solution showcases remarkable capabilities in early spoilage detection through the integration of image processing and machine learning within our smart IoT devices. This cutting-edge feature proactively identifies potential spoilage, thereby reducing waste and enhancing overall food safety.

The successful integration of our solution with cooling systems and transportation networks further emphasizes our commitment to reducing contamination risks and ensuring food quality throughout the supply chain. In addition, the provided tabulated results highlight the effectiveness of our approach in detecting food spoilage under different conditions. The accuracy, precision, recall, and F1-score metrics demonstrate that incorporating the MSMOTE technique significantly enhances the performance of our spoilage detection system.

In conclusion, our innovative approach, rooted in IoT technology and an accessible online platform, marks a pivotal step toward addressing food waste. As evidenced by the detailed tables and results, our solution holds the potential to revolutionize how we manage food resources, nourish communities, and establish a sustainable food ecosystem for the future.

References

[1] Rajesh Kumar Kaushal, Harini. T, Pavithra Lency.D, Sandhya.T, Soniya.P, "IOT BASED SMART FOOD MONITORING SYSTEM",ISSN (PRINT): 2393-8374, (ONLINE): 2394-0697, VOLUME-6, ISSUE-6, 2019,DOI: 10.21276/ijcesr.2019.6.6.14

[2] Gordana Ostojić, Stevan Stankovski,Srđan Tegeltija,Nikola Đukić,Branislav Tejić, "Implementation of IoT for food wastage minimisation",XVII International Scientific Conference on Industrial Systems (IS'17), Novi Sad, Serbia, October 4. – 6. 2017, University of Novi Sad, Faculty of Technical Sciences, Department for Industrial Engineering and Management.

[3] T. Bharath Kumar, Deepak Prashar, "Review on Efficient Food Waste Management System Using Internet of Things", International Journal of Current Research and Review,Int J Cur Res Rev | Vol 13 •

Issue 06 • March 2021, DOI: http://dx.doi.org/10.31782/IJCRR.2021.13603

[4] Diaa Salama Abdul Minaam, Mohamed Abd-ELfattah and Mona A. S. Ali,"Design of an Internet of Things (IoT) network system for Kitchen food waste management", IJCSNS International Journal of Computer Science and Network S 130 ecurity, VOL.18 No.5, May 2018

[5] Narender Chinthamu, R.Reka, B.Sundaramurthy, Rajendra Singh Bisht, Pilli. Lalitha Kumari, Amit Singh Rajput,"Iot-Driven Cold Chain Management: Ensuring Food Safety And Quality In Processing And Distribution", Eur. Chem. Bull. 2023, 12 (S3), 4843 – 4854 4843, DOI: 10.31838/ecb/2023.12.s3.543.

[6] Netra Shah,"Technology Adoption in Food supply chain management in developing countries: A Review", International Journal of Engineering and Advanced Technology (IJEAT), ISSN: 2249-8958 (Online), Volume-12 Issue-3, February 2023,DOI: 10.35940/ijeat.C3961.0212323

[7] Harshitha S, Mythreyi Manjunath H. K, Neha B. M, "IOT Based Food Spoilage Detector", ISSN: 2321-9653; IC Val+++ue: 45.98; SJ Impact Factor: 7.538,Volume 11 Issue VII Jul 2023- ©IJRASET:

[8] Thayagarajan M, Gurunadhan B, Dileep Kumar B, Ankitha K, Bhuvaneshwar P, Divya Sree C,"Smart Management of Food Storage and Waste Reduction", Journal of Electronics and Communication Engineering Research Volume 8 ~ Issue 5 (2022) pp: 24-29, ISSN(Online) : 2321-5941

[9] B Swathi,T Pooja,Punith S Kumar,Y Shankar and V Gowtham,"SURVEY ON IOT BASED FARM FRESHNESS MOBILE APPLICATION",XXX-X-XXXX-XXXX-X/XX/$XX.00 ©20XX IEEE,December8,2021, easychair pre-print.

[10] Dr. Prashant A. Athavale, Aayan Singh, Debanshu Poddar , Deepanshi Singh Rao,"Food Quality Monitoring System",International Journal of Engineering Research & Technology (IJERT) Vol. 11 Issue 07, July-2022

[11] Ekta Sonwani, Urvashi Bansal, Roobaea Alroobaea, Abdullah M. Baqasah and Mustapha Hedabou, "An Artificial Intelligence Approach Toward Food Spoilage Detection and Analysis",12 January 2022,doi: 10.3389/fpubh.2021.816226

[12] Divya bharathi.K, Rajalakshmi. M,"IOT BASED ON FOOD QUALITY DETECTION WITH BIO SENSOR TECHNOLOHY",© 2018 IJCRT,International Conference Proceeding ICLIASET 2018 March 2018| ISSN: 2320-28822nd International Conference on Latest Innovations in Applied Science, Engineering & Technology & IJCRT.ORG 2018

[13] Sahar Ahmadzadeh, Tahmina Ajmal, Ramakrishnan Ramanathan and Yanqing Duan, "A Comprehensive Review on Food Waste Reduction Based on IoT and Big Data Technologies", Sustainability 2023, 15, 3482. https://doi.org/10.3390/su15043482

[14] Vikas Nandeshwar, Srushti Bhuyar, Piyush Bhutada, Madhur Bhutada, Radha Bhutada, Vaibhav Bhuwaniya, Bhushan Berlikar, "Food Spoilage Detection System (FSDS) Using Arduino", © June 2023| IJIRT | Volume 10 Issue 1 | ISSN: 2349-6002, IJIRT 160553.

[15] Bhargavi Vijendra Sangam,Jayashree G R,Dr. Girish V.Attimarad,"Food Monitoring System Using Iot", Volume 7, Issue 7, July – 2022,International Journal of Innovative Science and Research Technology, ISSN No:-2456-2165,IJISRT22JUL1507.

[16] Dr. Dhananjay Matkedar, Rahila Fatima, Saima Danish, Syeda Tuba Mahvesh, Farzana Khanam, "Prototype for Cooked Food Quality Monitoring System using Application Based IOT Integrated System", International Journal of Research Publication and Reviews Vol (2) Issue (8) (2021) Page 367-371.

[17] Mahajan Nilambari Suresh, Mansuri Aqsa Salim, More Deepali Ashok, Lasure Aaishwarya Uttam, Prof Shaikh I. R., "IoT-Aided Charity: An Excess Food Redistribution Framework",ISSN: 2455-2631 © December 2019 IJSDR | Volume 4, Issue 12, IJSDR1912013 International Journal of Scientific Development and Research (IJSDR)

[18] Madhavi K Mallya, Niharika R, Niriksha P, Nisha K, B Sudha,"Food for Hunger: An IoT Aided Charity",International Research Journal of Engineering and Technology (IRJET),e-ISSN: 2395-0056, p-ISSN: 2395-0072,Volume: 07 Issue: 05 | May 2020

[19] Deep Singh, Khushwant Rajpurohit, Mayur Sevak, "IoT-Based Food Tracking and Management System Employing NodeMCU and the Blynk App",International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056, Volume: 10 Issue: 04 | Apr 2023, p-ISSN: 2395-0072

[20] J.Srinidhi,M.Nakshatra, P.Kavya,M.Ravi kumar, "IOT Based Food Spoilage Detection System using Arduino",@2022 JETIR July 2022, Volume 9, Issue 7, (ISSN-2349-5162),

[21] Jeyanthi S, Arun Kumar A, Muthu Rani M M, Rohini M I, Divya Jeyashree V,"IoT BASED FOOD WASTE MONITORING AND CONTROLLING SYSTEM",Journal of Pharmaceutical Negative Results ¦ Volume 14 ¦ Issue 3 ¦ 2023,DOI: 10.47750/pnr.2023.14.03.073

[22] Hilmy Prilliadi, "IoT and Smart Packaging: A Novel Approach for Managing Food Waste", Environment and technology role for Indonesia development. (191–207). DOI:10.55981/brin.538.c511 ISBN: 978-623-7425-85-4 E-ISBN: 978-623-7425-89-2.

[23] Ahmed, Mohammed & Hassanien, Aboul, "An Approach to Optimizing Food Quality Prediction Throughout Machine Learning",(2022),10.1007/978-3-031-13702-0_9.

[24] Sowmya Jagadeesan, Biswajit Barman, Ravindra Kumar Agarwal, Yashi,Srivastava, Barinderjit Singh, Sasmita Kumari Nayak, Nookala Venu,"A Perishable Food Monitoring Model Based On Iot And Deep Learning To Improve Food Hygiene And Safety Management", IJFANS International Journal of Food and Nutritional Sciences,© 2012 IJFANS. All Rights Reserved, UGC CARE Listed (Group -I) Journal Volume 11,Iss 8,Dec 2022.

[25] G.Sharada, S.Sindhoora, D.Sai Lakshmi Devi, Ms.PR Anisha, Dr.BV Ramana Murthy & Mr.C Kishor Kumar Reddy,"SMART STALE FOOD DETECTOR USING IOT (INTERNET OF THINGS)",Global Journal Of Engineering Science And Researches,ISSN 2348 – 8034, Impact Factor- 5.070

[26] Shazmina Gull, Imran Sarwar Bajwa, Waheed Anwar, and Rubina Rashid, "Smart eNose Food Waste Management System",Hindawi, Journal of Sensors, Volume 2021, Article ID 9931228, 13 pages, https://doi.org/10.1155/2021/9931228

[27] Pooja Sanap, Nilima Gunjal, Rutuja Markande, Aditi Patil, Shraddha Shinde, "Freshness of Food Detection using Internet of Things and Mobile Application – Result Based",Vol-7 Issue-3 2021 IJARIIE-ISSN(O)-2395-4396 14627

[28] Peerzada Shahzaib Parvez, Aditya Kumar Singh, Shrikant Thokre,"FOOD WASTAGE MANAGEMENT SYSTEM",DOI : https://www.doi.org/10.56726/IRJMETS34755,International Research Journal of Modernization in Engineering Technology and Science,05/Issue:03/March-2023, impact Factor- 7.868.

[29] Tamíris Pacheco da Costa,James Gillespie, Xavier Cama-Moncunill, Shane Ward, Joan Condell, Ramakrishnan Ramanathan and Fionnuala Murphy, "A Systematic Review of Real-Time Monitoring Technologies and Its Potential Application to Reduce Food Loss and Waste: Key Elements of Food Supply Chains and IoT Technologies", Sustainability 2023, 15, 614. https://doi.org/10.3390/su15010614

[30] Nemade, B., Shah, D. (2023). An IoT-Based Efficient Water Quality Prediction System for Aquaponics Farming. In: Shukla, A., Murthy, B.K., Hasteer, N., Van Belle, JP. (eds) Computational Intelligence. Lecture Notes in Electrical Engineering, vol 968. Springer, Singapore. https://doi.org/10.1007/978-981-19-7346-8_27

[31] Agrawal, S.A., Umbarkar, A.M., Sherie, N.P., Dharme, A.M., Dhabliya, D. Statistical study of mechanical properties for corn fiber with reinforced of polypropylene fiber matrix composite (2021) Materials Today: Proceedings,. Umbarkar, A.M., Sherie, N.P., Agrawal, S.A., Kharche, P.P., Dhabliya, D. Robust design of optimal location analysis for piezoelectric sensor in a cantilever beam (2021) Materials Today: Proceedings, .