Food wastage Analysis Framework using Comprehensive IoT-Based Multi-Sensor

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ABSTRACT

Wasting of food is a key issue in most parts of the world, which is associated with losing food nutrition, health risks, and the environment. Ineffectiveness of the currently used detection means is an indication that there is need to have intelligent and real-time monitoring mechanisms. In this work, an IoT-based multi-sensor system incorporating NDIR CO 2, DHT 22, and MQ-4 sensors to detect and predict the presence of important environmental indicators (carbon dioxide, temperature, humidity, and methane concentration) will be proposed to monitor food spoilage. The cloud-based machine learning methods are used to process sensor data to classify the freshness state of food products. Prediction was confirmed by experimental validation of the system on different fruits, vegetables, and foodstuff with an overall accuracy of 95% supporting the reliability of the system. The introduced framework provides a scalable and effectual solution for reducing food waste, enhancing food safety, and improving supply chain sustainability.

Keywords: Food Wasted detection, NDIR Co2 sensor, DTH22 sensor, MQ-4 sensor, IoT, Artificial Intelligence

1. Introduction

Recently, there seems to have been a rise in concern towards food waste thus research towards reducing the various effects that surround it [1]. According to the Global Report on nutrition, it was estimated that nearly 19% of the global population has a poor intake of nutrients and is associated with malnutrition and increased mortality level especially among children below the ages of five years this is 35%. Food wastage was equally a critical factor that worsened this problem affecting the Hunger Index and the environment. Nearly 3.1 million children each year lost their health because of the poor nourishment, making this issue remain critical [3]. Some of the areas that it was noted that excessive food portions were thrown away were restaurants, hostels, during parties and at home and some of the highlighted causes of the vice include; poor planning and ordering of meals and foodstuffs, over-purchasing of foods that do not meet marketing targets and inefficient handling of the foods. This unethical practice has been considered socially and environmentally irresponsible, supported by evidence from the Food and Agriculture Organization (FAO), which revealed that nearly one-third of the food produced globally is wasted [4]. Modern technologies continue to advance daily, influencing various sectors such as the medical field, particularly its diagnostic aspects, as well as health and food safety domains. Enhancing diagnosis involves correlating patients' health conditions with data gathered from diverse health analysis technologies. [5,6]. The intelligent food traceability has been identified to play an important role in resolving global problems related to food omics, namely, the overall analysis of food properties such as nutritional content, quality, authenticity, safety, and security [7]. Food may go bad in many different ways, such as microbial activities such as bacteria, molds and yeasts being present on food leading to wastage (ex. bread left at room temperature must not mold). Fruits and vegetables undergo enzyme reactions that cause wastage like over ripe and mushy bananas. Fats and oils may also become rancid due to chemical processes, such as oxidation, which change taste and smell (e.g. nuts growing stale). Physical injuries, including bruises on fruits, like apples, can result in exposures to microbes. Foods with high moisture levels are likely to allow the growth of mold (e.g. bread in damp conditions). Storing the perishable goods that cannot be refrigerated like milk in the right conditions will result in bacterial growth and wastage as exhibited in Figure 1.

Traditional means of food spoilage detection like manual examination and chemical analysis are frequently tedious, subjective and is limited in scalability. This weakness has led to the utilization of advanced technologies such as IoT and AI, and sensor networks into food quality evaluation systems. Sensing IoT solutions permit remote and constant tracking of all the environmental parameters like temperature, humidity, and gas concentration to identify the signs of spoilage. When coupled with machine learning algorithms, these technologies is designed to analyse complex data patterns to forecast food degradation before it becomes visible, reducing losses across the supply chain and ensuring safer consumption.

The IoT sensors are recognized for its reusability and potential to substitute the traditional analysis method using quick, accurate, reliable, and multiplex analysis. There are quite a number of outstanding contributions in the area of biological sensing devices in food safety and inspection such as the detection of food borne pathogens in contaminated food in ports. The fundamental concept of biosensor detection is to combine a biological recognition unit coupled with a sensing transducer which emits a detectable signal directly related to the analyte concentration. Multiple forms of biosensing devices have been constructed as determined by the type of bioreceptor, but their role can depend on the interaction with analytes, and it must exhibit high specificity [8]. Alternatively, the most common form of biosensor in terms of type of transducer is the electrochemical type with the rest being optical and mass-sensitive biosensors [9].

The system suggested is described in the following details. Part 2 follows a literature review, providing the overview of the past studies and approaches. Section 3 will be the proposed approach, clarifying the new techniques and mechanisms used. Section 4 comments on the results, offering the evaluation of the outcomes and implications thereof. Lastly, Section 5 provides the deduction, which summarizes the results and proposes the directions.

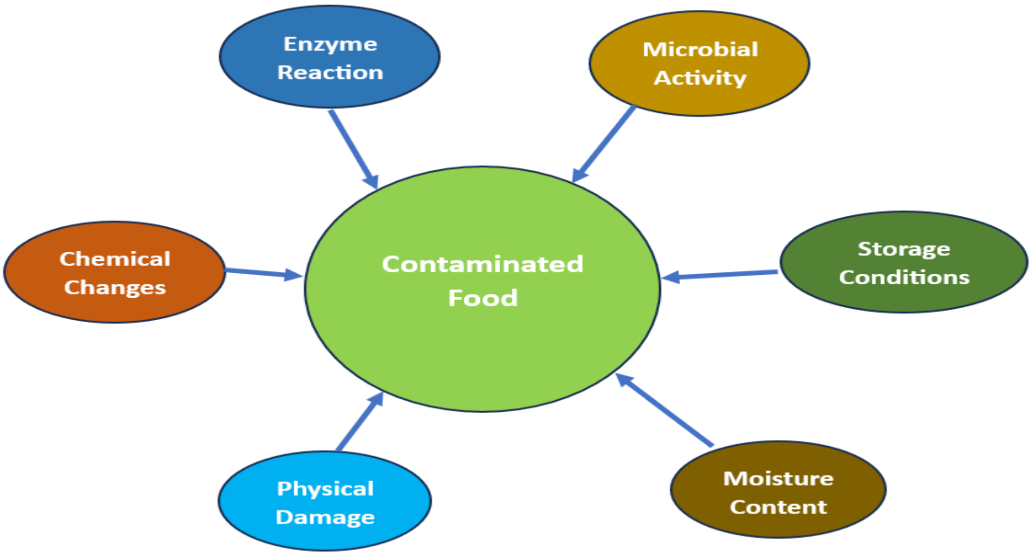

Figure 1. Various ways to spoil food

2. Related Works

In this era, food wastage is a major problem in the world even with the technological and food preservation systems. Vakkas Doğan, et al, [10] proposed a novel colorimetric system in sensing images through red cabbage extract (ARCE), a smartphone application that incorporates embedded machine learning to monitor real time food wastage. FG-UV-CD100 films were originally prepared through crosslinking of ARCE-impregnated fish gelatine (FG) in the presence of carbon dots (CDs) in the presence of UV light. Changes of colour of FG-UV-CD100 films to ammonia vapor samples with graded concentration levels were recorded under varying light conditions (through smartphones of different brands) and this produced a heterogeneous and representative dataset that was used to train the machine learning classifier.

Byeong M. Oh, et al,[11] made an organic chemo sensor probe called DEAH dimethylcyclohex-1-en-1-yl)vinyl)-N,N-diethylbenzenamine chloride that is able to identify amines with the ability to respond in two different modes like colorimetric and fluorometric changes. Feiyi Chu, et al, [12] Presented a strategy involve the pKa manipulation in order to address the problem leading to logical development of high-efficiency colorimetric and fluorescent sensor, CFB-H2S, that is capable of functioning within a wide pH range of 6.0-10.0. Noteworthy, the sensor is highly sensitive with a wonderful signal-noise ratio of 81-fold which also offers great advantages to the applications of detecting H2S. Test strips were made successfully, and their utility in real life was also validated in the case of food wastages. Jingjiang Lv, et al, [13] had been suggested a versatile TEG-based multifunctional information interaction system, leveraging body heat to facilitate information exchange via finger touch. To enhance energy conversion efficiency, the flexible TEG was said to achieve superior performance enhancement via tuning of the filling factor and material thermal properties, resulting in a normalized power density of 1.43 $\mu W/cm^2 K^2$. As a proof-of-concept, the system was employed in food systems wastage nursing, utilizing an MXene-based sensor to attain reliable and highly efficient detection of ammonia.

In response to the urgent need for high-performance volatile amine-sensitive sensors used across food, healthcare, and environmental domains, Jian-Hao Zhao, et al [14] proposed an advanced fluorescent sensing probe. This probe, based on an indacenodithiophene structure with a π-conjugated system, was designed and synthesized to address these requirements. Xianghong Xie, et al, [15] proposed a strategy, stated that Fluorescein isothiocyanate (FITC) was used as an indicator by being mixed with Eu/SA nanoemulsion and then physically applied to a commercial filter membrane to create intelligent fluorescent labels. The freshness of shrimp, both with and without the Eu/SA nanoemulsion coating, was monitored using a non-contact tagging method. Yong Gao,et al,[16] had been developed a novel rhodol-based fluorescent probe, RSMA (formyl-rhodol Schiff base with methoxyaniline), for the detection of putrescine. Furthermore, RSMA was successfully fabricated into solid-state sensors for on-site putrescine detection in shrimp, demonstrating its practical deployment in monitoring food quality wastage.

Hydrogen sulfide (H2S), a common hazardous gas, endangers the assessment of water and food safety parameters. To address this issue, Wenjuan Cai, et al, [17] created and characterized an innovative near-infrared fluorescence probe designated as DTCM, through Xray diffraction study on single crystals for the detection of H2S. Maria Maddalena Calabretta, et al, [18] presented an easy-to-use colorimetric sensing paper capable of detecting biogenic amines with the naked eye. The sensing compound is aglycone genipin, a natural cross-linking agent derived from gardenia fruit, which binds to biogenic amines and produces water-soluble blue pigments. Yuqing Qin, et al, [19] A biosensor based on Bacillus subtilis spores was introduced for the rapid, highly sensitive, and visual detection of biogenic amines. This innovative system, integrated with smartphone-based analysis for real-time histamine monitoring.

Alexander Altmann, et al, [20] have developed a porphyrin-derived sensing membrane designed for detecting biogenic amines. This porphyrin-based sensor is incorporated into mesoporous silica. Sensitivity to medium humidity level was negated by dispersing the modified silica in polyethylene (PE), then thermally extruding it into PE films. Jing Liu, et al, [21] had presented a bioelectronic olfactory system based on MXene and hydrogel for highly sensitive detection of liquid and gaseous hexanal, a distinctive odor compound found in wasted food. The conducting MXene/hydrogel architecture was established on a sensor through physical adsorption. Zahra Mohammadi, et al, [22] examined the sensory characteristics of nanomaterials, encompassing metallic and magnetic nanoparticles, carbon nanostructures such as nanotubes, graphene and its derivatives, and nanofibers produced via electrospinning. Ricarda Torre, et al, [23] proposed a Sensor technology utilizing screen-printed electrodes (SPEs) have become more prominent due to their beneficial attributes, such as user-friendly operation and mobility, enabling rapid analysis in point of need scenarios. Utilized insights from various existing methods for detection of food wastage using various Internet of Things and Bio sensors.

3. Developed Methodology

Identification of wasted food is an issue that is constantly causing problems to food industries across the globe. Old methodologies like visual inspection and smell though used to, fail in reliability to detect at early stages wastage. As an example, a large food processing facility can be considered, and several loads of fresh produce are processed daily. There are cases where despite the stringent steps implemented to provide quality control and assurance, slip-ups will occur primarily due to the human factor or the variation of our senses in terms of smell, feel, sight etc. with others of the inspectors. Still, one must mention that a lot of problems are related to the further evolution of this technology which can be anticipated in the future: To start with, the sensor and data analysis systems can be optimized in the future which can result in more efficient wastage detection. The most recent developments, including the MIL-125-based bimetallic oxide sensors suggested by Li et al, [4] may be taken as an example of the manner in which nanocomposition design can increase signal sensitivity and the effectiveness of detection, which justified the approach of multi-sensor optimization chosen in the given work. The industry will thus aim at enhancing the properties of the sensors and the algorithms with which the data will be analyzed to address the issue of accuracy in detecting the food products that are wasted and minimize the wastage. It also says a lot about the pursuit of a new innovation in the existing food safety process in order to ensure that the consumers are served with fresher products, which are safe to consume as well as improving the productivity of the operations. The proposed A Comprehensive IoT-Based Multi-Sensor Framework To Predict Food Wastage Analysis is as follows as shown in the Figure 2 below.

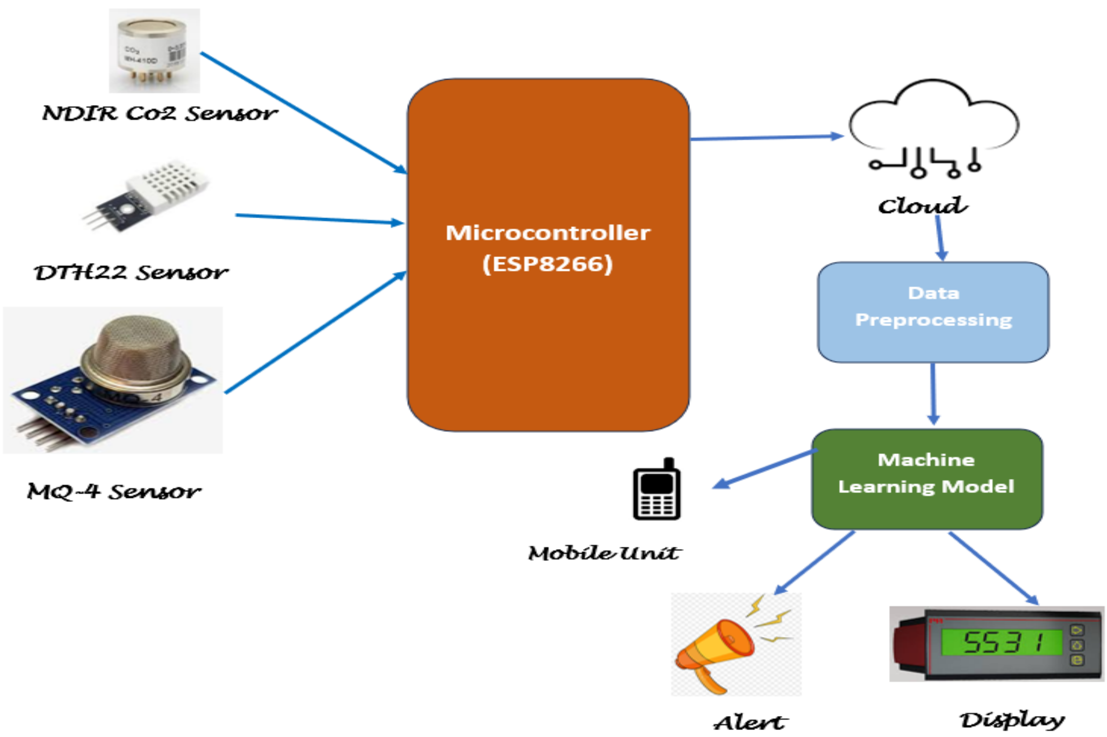

Figure 2. Architecture of Proposed Model

The suggested system involves the combination of IoT-powered sensors and cloud analytics to improve the visualization of food spoilage. The hardware setup consists of an NDIR CO 2 sensor to measure the concentration of carbon dioxide, a DHT22 sensor to measure temperature and humidity, and an MQ-4 sensor employed to quantify methane levels an indicator of anaerobic decomposition. These sensors are able to capture real time information that is sent wirelessly to an IoT cloud service through an ESP8266 microcontroller. To make the data accurate, the collected data are subjected to various preprocessing stages such as noise filtering, normalization and calibration. Machine learning algorithms are then applied to classify food items as fresh, lightly wasted, or spoiled. This integrated architecture enables continuous monitoring, early detection, and automated alert generation to minimize food losses and maintain product quality.

The data then goes through several preprocessing steps once it gets into the cloud to make it more reliable and reliable for its users [24]. Machine learning is of two types which are the supervised learning and the unsupervised learning algorithms [25]. food freshness data and a buzzer activation model. If there are signs of food wastage, changes in the CO_2 or methane level, during testing, the system gives a continuous buzzer sound [26]. At the same time, the threshold and the current reading is displayed, it gives feedback to the users and the users can monitor the food status through an application. On the contrary if the foods stay fresh as they are, the system beeps once using the buzzer and shows the current values on the sensors which is fit for consumption. It enhance food safety as well as management but also improves operations and reduces wastage through proper spoils identification at the earliest time [27].

3.1. NDIR Co2 Sensor:

An NDIR CO_2 sensor is one that can measure the concentration of carbon dioxide in food through the use of infrared light at a particular wave length. In this process, a CO_2 sensor placed in the food environment uses light to penetrate through the molecules of the gas and, when these molecules are illuminated, the amount of transmitted light diminishes. This is due to the fact that dissolution of CO_2 reduces with a decrease in its concentration present in solution. The sensor then then determines the state of the gaseous mixture by using the Beer-Lambert's law which is a simple method that tells us the amount of light absorbed by a gas in relation to the concertation of the gas. In food storage and processing atmosphere, high concentrations of CO_2 usually signify the wastage caused by activity or chemical reactions from microbes [28]. Real-time monitoring by the NDIR sensor helps in early detection of the wastage hence enhancing food quality and food safety. This technology is important as it is used for detection of spoilt products that are not in a condition that can be consumed hence helpful in the management of food supply chain [29].

Early spoilage detection: Might require continuous or hourly monitoring to catch changes.

Routine quality control (e.g., after transport): A single measurement after 12–24 hours in transit may be sufficient.

Safety assessment (e.g., risk of toxic buildup): Monitoring over the entire transport duration is recommended.

CO_2 from produce is measurable within hours. Volatile spoilage gases (H_2S, amines, ammonia, VOCs) usually need 12–48 hours to reach detectable levels, depending on conditions.

The functionality of an NDIR CO_2 sensor with regards to the absorption of an infrared light. The main principle of this experiment is that it is based on Beer-Lambert's law which is described by the following mathematic al equation (1);

$$\frac{I_{transmitted}}{I_{incident}} = e^{-\alpha.L.C} \tag{1}$$

Where:

- $I_{transmitted}$ is the intensity of transmitted light through the sample.
- $I_{incident}$ is the intensity of incident (initial) light.
- α is the absorption coefficient of the gas (CO_2 in this case).
- L is the path length of the light through the gas sample.
- C is the concentration of the gas (CO_2 concentration).

The optical absorption coefficient α also depends on the spectral intervals of the light produced by the NDIR sensor and physical-chemical characteristics of CO_2. When sensor receives the values of $I_{transmitted}$ and $I_{incident}$, through the formula above, it can determine the value of C which signifies the degree of CO_2 concentration in the sampled air. Thus, this calculation makes it possible for the sensor to capture and transmit the value of CO_2 in real-time to indicate when the food is spoilt, or to keep stock of quality in other industries or environments.

3.2. DTH22 Sensor:

The DHT22 sensor serves a crucial function in detecting food wastage by determining the temperature and humidity the food stored in a particular environment. These two factors are very significant in influencing the growth rate of wastage microorganisms which includes bacteria and Mold. The sensor provides digital readings of the temperature and the relative humidity that can be employed in order to control the temperature in order to extend the shelf life of the food products.

Relative Humidity (RH) :

The DHT22 sensor directly provides the relative humidity (RH) as a percentage:

$$\text{RH} = \frac{Water\ vapour\ pressure}{Saturation\ vapour\ pressure} * 100 \qquad (2)$$

Temperature (T) :

The sensors measures temperature in Celsius, which can be converted into Fahrenheit.

$$T_F = T_C * \frac{9}{5} + 32 \qquad (3)$$

Where, T_F is the temperature in Fahrenheit and T_C is the temperature in Celsius.

Dew Point (Td):

The dew point, indicating the temperature at which air become saturated with moisture, can be calculated using the following equations:

$$\propto (T, RH) = \frac{17.27 * T}{237.7 + T} + ln(RH/100) \qquad (4)$$

$$T_d = \frac{237.7 * \propto (T, RH)}{17.27 - \propto (T, RH)} \qquad (5)$$

Where, T_d is the dew point temperature, T is the current temperature in Celsius, and RH is the relative humidity as a percentage.

Heat Index (HI):

The heat index, reflecting the perceived temperature considering humidity, can be approximated using:

$$\text{HI} = \text{T}-((0.55-0.0055*\text{RH})*(\text{T}-14.5)) \qquad (6)$$

here, *T* refers to temperature in Celsius, while *RH* indicates relative humidity as a percentage.

3.2. MQ-4 Sensor

The MQ-4 sensor measuring methane (CH4CH_4CH4) levels In a food, a gas produced during the anaerobic decomposition of organic matter by microorganisms. Spoiled food that is stored in low oxygen conditions causes greater activity of anaerobic bacteria resulting in an increase in methane emissions. These emissions are sensed by the MQ-4 sensor and give an indication of the wastage.

The MQ-4 sensor provides an analogue signal as output which is associated with the concentration of methane in the air. The correlation between the sensor resistance (Rs) and the methane concentration (CCH 4) may be expressed in terms of the sensor sensitivity characteristics, which is normally indicated on the sensor datasheet. This correlation is most frequently logarithmic and may be written as:

$$\text{Log}\left(\frac{R_S}{R_0}\right) = -a\, log(C_{CH4}) + b \tag{7}$$

Where, R_s is the sensor resistance at the detected methane concentration, R_0 is the sensor resistance in clean air, C_{CH4} is the methane concentration, a and b are constants specific to the sensor, obtained from the calibration curve.

By rearranging this equation, the methane concentration can be derived:

$$C_{CH4} = 10^{\left(\frac{b - log\left(\frac{R_S}{R_0}\right)}{a}\right.} \tag{8}$$

To monitor food wastage, the microcontroller was used to receive raw data provided by the DHT22 sensor (measuring temperature and humidity), the NDIR CO 2 sensor (measuring carbon dioxide levels) and the MQ-4 sensor (measuring methane levels). This data is relayed to a cloud platform using an inbuilt Wi-Fi technology. Before analysing, preprocessing has been done and includes noise filtering, calibration, normalization, aggregation and error checking. This preprocessing makes the pre-processed data to be accurate, consistent, and can be used in the analysis that will follow, making it easy to monitor the process and intervene in a timely manner to stop wastage of food.

3.3. Preprocessing:

Apache Spark and PySpark, in our research, Apache Spark is a powerful distributed computing platform which enables you to run large data with efficiency. PySpark, the Python API for Spark, provides a seamless way to use Spark with Python. When preprocessing data using PySpark, can perform various transformations and actions to clean and prepare data for machine learning tasks.

3.3.1. Loading Data: PySpark had read data obtained from diverse sources, such as AWS. Data is typically ingested into a Spark DataFrame, a distributed tabular dataset defined by named columns.

3.3.2. Data Cleaning: Data Cleaning involves 2 techniques. Such as (i) handling missing values and removing duplicates.

3.3.3. Data Transformation: Features are normalized to a standard range using methods such as Min-Max Scaling or Standard Scaling.

Min-max scaling: Min–Max normalization transforms feature values into a specified range, typically [0, 1] or [-1, 1].

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{9}$$

Where, X is the original feature value. X_{min} is the minimum value of X in the dataset, X_{max} is the maximum value of X in the dataset.

Standard Scaling (Z-score normalization): Standard scaling transforms features to have a mean of 0 and a standard deviation of 1.

$$X_{scaled} = \frac{X - \mu}{\sigma} \tag{10}$$

Where, X is the original feature value, μ is the mean of X in the dataset, σ is the standard deviation of X in the dataset.

Algorithm

```
df = spark.read.csv("s3a://bucket_name/data.csv", header=True, inferSchema=True) //
Loading data

mean_value = df.select(mean(df['column_name'])).collect()[0][0]
```

df = df.fillna(mean_value, subset=['column_name']) // Handling Missing Values

df = df.dropDuplicates() // Removing Duplicates

scaler = MinMaxScaler(inputCol="features", outputCol="scaledFeatures") // min-max Scaling

OutputCol="scaledFeatures", withStd=True, withMean=True) //Standard Scaling

encoder = OneHotEncoder (inputCol="categoryIndex", outputCol="categoryVec) // encoding

train_df, test_df = df.randomSplit([0.8, 0.2], seed=42) // Splitting data

3.4. Random Forest Algorithm

The Random Forest algorithm is a versatile and powerful ensemble learning method, it is a commonly employed algorithm in machine learning for both classification and regression, functioning by building multiple decision trees and aggregating their outputs as either the mode (for classification) or the mean (for regression). In the Random Forest model, each tree is constructed with the random sample of the training dataset, and at the time of splitting, considers random features. Once the data has been pre-processed, it is then split into two parts: a training set and a testing set to find out its accuracy of the system. The given dataset is divided into the training set and the testing set, where 75% of the dataset is being used for training the Random Forest and the rest 25% is used for accessing the model's performance. This prospect also guarantees that the model has enough data training to make the required patterns and relationships discernible and, at the same time, maintain the chance of testing out its accuracy and proficiencies on new data not used in its training. It enables one to determine the ability of the model to generalize data which are new and unknown which are always crucial in judging the reliability and accuracy of the proposed model in practical applications.

Splitting Process: In order to give a formal definition of how the data set is splitted into train set and test set, we define the notation as follows.

$$\text{Train set} = \{(x_i, y_i) | i = 1,2,\ldots\ldots, train\ size * N\} \quad (11)$$

$$\text{Test set} = \{(x_i, y_i) | i = train\ size * N + 1, \ldots, N\} \quad (12)$$

Here, x_i represents the input features (or independent variables) and y_i represents the corresponding target values (or dependent variables).

This also tends to discourage overfitting and also increase the amount of robustness in the model. Random Forests are particularly popular as they can work with the large number of predictor variables and with noisy data. Especially, they are easier to be tuned and have less overfitting risk compared with IDT, which are widely applied in fields of finance, health and ecology.

3.5. Alert:

An application has been developed for android operating system for testing and monitoring of the environmental factors that affect the freshness of food and wastage. This application was created with the sole purpose of generating testing values for temperature, humidity, methane, and carbon dioxide in real-time. If it matches the monitored food with that of what was stored in the refrigerator and were declared fresh, then the current values of each parameter are shown on the screen and a small beep sound is heard, signifying that the food is safe for consumption. On the other hand, if the food is, for instance, found to be spoilt, then the application reveals to the user the recommended threshold values of the parameters and the actual output values of the parameters that went high or low. Moreover, in the event of wastage, the application generates an unbroken sound to inform the user about the quality of food that has gone bad. The application will allow seeing a bright and direct signal of the quality of the food, and the use of audio-visual effects will increase the usability and efficiency of the wastage detection system.

4. Experimental setup

The objective of this experiment is to monitor and analyze the environmental conditions (temperature, humidity, CO_2, and methane gases) for various fruits and vegetables.

4.1. Dataset

We used the Random Forest method to train a model based on a dataset of 28 vegetables/fruits (apples, bananas, carrots, beetroot, cabbage, peas, beans, okra, grapes, watermelon) available at Table 1 and 20 common foods (bread, milk, cheese, yogurt, butter etc.) at Table 2. Each group was defined by the particular environmental conditions of its temperature, humidity, methane, and carbon dioxide in degree Celsius, Percentage and parts per million (ppm) respectively.

Table 1. Environmental Threshold Values for Common Fruits/Vegetables

S.No	Fruits/ Vegetables	Temperature (°C)	Humidity (%)	CO_2 (ppm)	Methane (ppm)
1	Apple	1-4	90-95	500-1500	0-10
2	Banana	13-16	85-90	1000-3000	0-5
3	Orange	4-7	85-90	500-2000	0-8
4	Tomato	10-25	85-95	500-3000	0-15
5	Potato	4-10	80-90	500-2000	0-10
6	Carrot	0-4	90-95	500-2500	0-8
7	Cucumber	10-15	85-95	500-2000	0-12
8	Spinach	0-4	90-95	500-1500	0-5
9	Broccoli	0-4	90-95	500-2000	0-8
10	Strawberry	4-10	90-95	500-1800	0-10
11	Pineapple	10-15	85-90	800-2500	0-5
12	Grapes	0-4	85-90	500-1800	0-8
13	Watermelon	10-15	80-85	800-3000	0-5
14	Brussels sprouts	0-4	90-95	500-1800	0-8
15	Cerely	0-4	90-95	500-2000	0-5
16	Egg Plant	10-15	85-90	500-2500	0-12
17	Green Beans	0-4	90-95	500-2000	0-8
18	Peas	0-4	85-90	500-1500	0-10
19	Artichoke	5-10	85-90	500-1800	0-5
20	Radish	0-4	90-95	500-2000	0-8
21	Cabbage	0-4	90-95	500-2500	0-10
22	Beetroot	0-4	85-90	500-2000	0-5
23	Leek	0-4	85-90	500-1500	0-8
24	Sweet Potato	10-15	80-85	800-2500	0-5
25	Pumpkin	10-15	80-85	800-3000	0-10
26	Swiss Chard	0-4	90-95	500-2000	0-8
27	Kale	0-4	90-95	500-1800	0-12
28	Okra	10-15	85-90	500-2500	0-10

Table 2. Environmental Threshold Values for Common Food Items

S.No	Food Items	Temperature (°C)	Humidity (%)	CO_2 (ppm)	Methane (ppm)
1	Bread	20-25	40-50	400-800	0-2
2	Milk	1-4	85-90	400-800	0-5
3	Cheese	2-6	70-80	400-800	0-2
4	Yogurt	1-4	85-90	400-800	0-3
5	Butter	5-10	40-50	400-800	0-2
6	Eggs	1-4	70-80	400-800	0-5
7	Chicken	0-4	85-90	400-800	0-8
8	Beef	0-4	70-80	400-800	0-10
9	Fish	0-4	85-90	400-800	0-5
10	Shrimp	0-4	85-90	400-800	0-3
11	Potatoes	5-10	80-90	400-800	0-8
12	Rice	20-25	40-50	400-800	0-2

13	Pasta	20-25	40-50	400-800	0-2
14	Flour	20-25	40-50	400-800	0-2
15	Oats	20-25	40-50	400-800	0-2
16	Chocolates	15-20	40-50	400-800	0-2
17	Honey	15-20	40-50	400-800	0-2
18	Nuts	15-20	40-50	400-800	0-2
19	Canned Foods	20-25	40-50	400-800	0-2
20	Frozen Foods	-18 to -15	80-90	400-800	0-2

In establishing how much of the fruits, vegetables and common food items can go to waste, we have developed a sequence of conditions depending on the jointness of environmental conditions such as temperature, humidity, methane and carbon dioxide. An example would be Scenario 1, according to which, when CO 2 and methane are beyond their respective thresholds, this would be a good sign to show that the food is likely to go to waste. In Scenario 2, when the level of humidity and temperature is high, but the amount of CO 2 and methane is under the acceptable limits the food may still be fresh, but this state of affairs is an indication that wastage will soon follow unless the environmental parameters are modified as soon as possible. Scenario 3 takes into account that when two of the parameters like CO 2 and temperature go beyond their limiting values, this may be as a sign of wastage, despite the other two parameters of humidity and methane being within acceptable limits. These scenarios indicate the complexity of the interaction between various environmental factors as concerns food wastage and the necessity to monitor various parameters in terms of food quality and freshness as well as other stored products and items.

4.2. Required components and Implementation model

In this study, we utilized several hardware components, including an NDIR CO_2 sensor, a DHT22 sensor, an MQ-4 sensor, a WiFi-inbuilt microcontroller, a buzzer, display and Mobile unit.

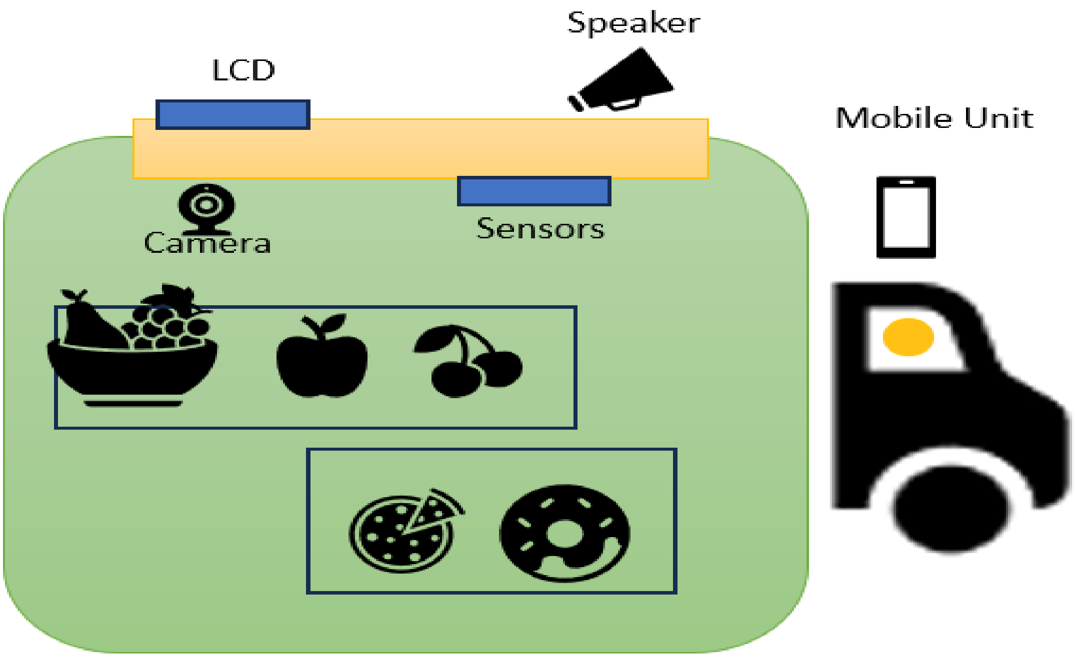

Figure 3. Implementation of Proposed Innovation

The software requirements for this project included AWS Cloud for data storage and processing, Apache Spark and PySpark for data preprocessing, and the Random Forest machine learning algorithm for model training and prediction. The system was run on an i5 processor with 64 GB of RAM to ensure efficient handling of the computational workload.

Figure 3, representing the implementation of proposed innovation. The food transferring from one area to another area in a container. Device placed in a container integrated with speaker and LCD. When the food going to damage, our device detects the food wastage and automatically send alert through producing sounds and as well as displays the actual readings and threshold readings. Along with the truck driver can access the status of food through mobile unit.

4.3. Performance metrics:

Accuracy**:** Accuracy measures the proportion of correctly predicted instances out of the total instances.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{13}$$

Precision: Precision measures the proportion of correctly predicted positive instances out of all instances predicted as positive.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{14}$$

Recall**:** Recall measures the proportion of correctly predicted positive instances out of all actual positive instances.

$$\text{Recall} = \frac{TP}{TP+FN} \tag{15}$$

F1 Score: The F1 Score is the harmonic mean of precision and recall, providing a single metric that balances both.

$$\text{F1 Score} = 2\times\frac{Precision * Recall}{Precision + Recall} \tag{16}$$

Where, TP indicates True Positives, TN indicates True Negatives, FP indicated False Positives and FN indicated False Negatives.

ROC-AUC (Receiver Operating Characteristic - Area Under Curve): The ROC-AUC score represents the area under the ROC curve, which plots the true positive rate (Recall) against the false positive rate (1 - Specificity).

$$\text{AUC} = \int_0^1 TPR(t)\ dEPR(t) \tag{17}$$

Where, TPR(t) representsTrue Positive Rate at threshold t, FPR(t) represents False Positive Rate at threshold t.

4. Result

We did a thorough experiment on the different vegetables, fruits, and other general food stuffs depending on the environmental conditions in terms of temperature, humidity, CO 2 and methane content. Apached Spark and PySpark were used to pre-process the data collected by bringing it together and received by the sensors to handle it efficiently. The training and testing of the model were done with the aid of the Random Forest algorithm whose accuracy is enormous, of 95%. Such high precision is what highlights the credibility of the model in predicting food wastage and freshness. We have effectively tested the combination of the state-of-the-art data processing and machine learning methods, which can greatly benefit the improvement of food quality and safety evaluation.

Table 3. Analysis of Environmental Parameter Measurements on Vegetables and Fruit

S.No	Fruits/ Vegetables	Temperature (°C)	Humidity(%)	CO_2 (ppm)	Methane (ppm)	Stage
1	Apple	3	92	1600	11	Wasted
2	Banana	17	95	1500	3	Lightly wasted
3	Orange	5	87	1500	6	Fresh
4	Tomato	30	93	3200	19	Wasted
5	Potato	6	89	1700	5	Fresh
6	Carrot	8	92	2800	8	Wasted
7	Cucumber	13	89	2500	17	Wasted
8	Spinach	9	99	2500	9	Wasted
9	Broccoli	3	92	1200	1	Fresh
10	Strawberry	6	97	1800	11	Fresh
11	Pineapple	13	87	2800	9	Wasted
12	Grapes	9	95	1500	7	Lightly wasted
13	Watermelon	10	80	800	2	Fresh
14	Brussels sprouts	8	99	2800	22	Wasted
15	Cerely	2	91	1000	4	Fresh
16	Egg Plant	8	89	2400	11	Fresh
17	Green Beans	21	189	3000	15	wasted
18	Peas	15	105	1300	8	Lightly wasted
19	Artichoke	17	108	2290	19	Wasted
20	Radish	2	93	1000	6	Fresh

21	Cabbage	8	99	1500	7	Lightly Wasted
22	Beetroot	3	87	500	4	Fresh
23	Leek	9	98	1700	21	Wasted
24	Sweet Potato	18	89	2200	3	Lightly Wasted
25	Pumpkin	20	100	3500	18	Wasted
26	Swiss Chard	3	93	1500	8	Lightluy wasted
27	Kale	3	92	51500	10	Fresh
28	Okra	19	99	2000	8	Lightly wasted

The table 3 gives a breakdown of the measurement of the environment parameters (temperature, humidity, CO 2 and methane concentration) and how they affect the wastage of different fruits and vegetables. A high level of CO 2 and methane, as well as high humidity, is usually linked to wastage. As an example, tomatoes and pumpkin have high levels of CO 2 and methane implying wastage, whereas fruits such as oranges and potatoes which have lower levels of CO 2 and methane are still fresh. Broccoli and radish are the vegetables that retain their freshness with low temperature and humidity. Interestingly, there are other items such as kale and artichoke that show different readings, implying that there are other variables that can affect wastage.

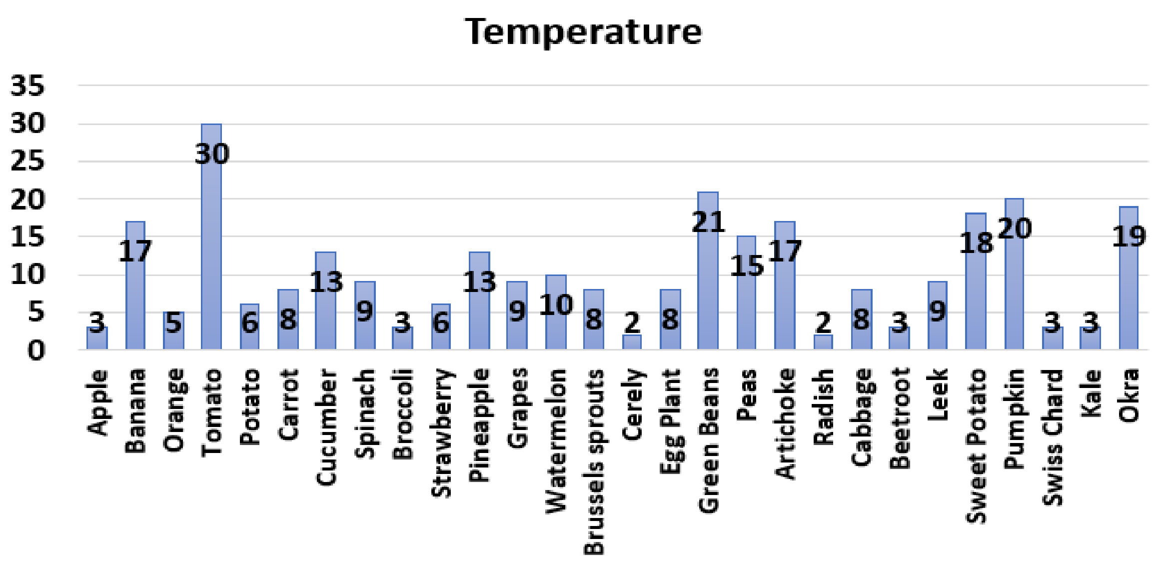

Figure 4. Temperature variation of fruits and vegetables under storage conditions

Various temperature conditions for different fruits and vegetables shown in Figure 4, illustrated that During testing period, we got cerely and Radish exhibits very low temperature as compared to other vegetables and fruits. Tomato exhibits with a high temperature among the all.

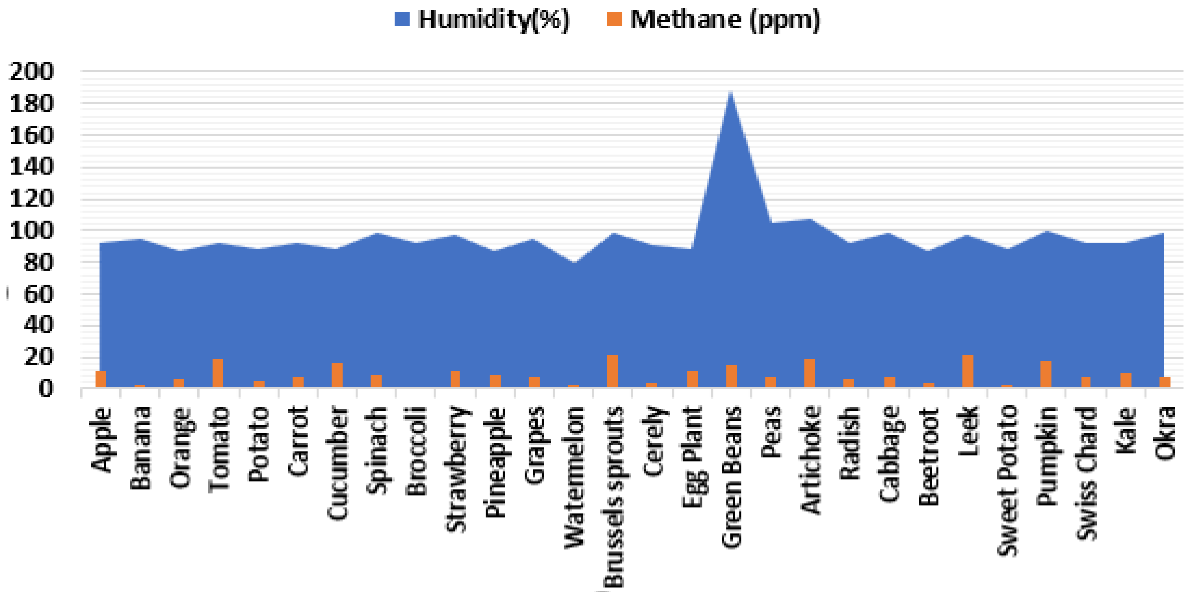

Figure 5. Humidity (%) and Methane (ppm) levels in fruits and vegetables

Graphical representation of humidity (%) and methane (ppm) in various vegetables and fruits represented in Figure 5, illustrating that high-humidity vegetables like Spinach and Brussels sprouts show increased methane levels, indicating potential wastage risk. Conversely, fruits like Watermelon have lower humidity and methane levels, suggesting better stability. Elevated methane in Tomatoes and Artichokes may signal active ripening, while lower levels in Broccoli and Potatoes reflect more stable conditions.

Table 4. Analysis of Environmental Parameter Measurements on common food items

S.No	Food Items	Temperature (°C)	Humidity(%)	CO_2 (ppm)	Methane (ppm)	Stage
1	Bread	28	60	850	8	Wasted
2	Milk	2	88	600	3	Fresh
3	Cheese	8	90	600	1	Lightly Wasted
4	Yogurt	6	90	1000	3	Wasted
5	Butter	19	70	1000	5	Wasted
6	Eggs	2	75	500	3	Fresh
7	Chicken	2	87	600	6	Fresh

8	Beef	11	100	1050	28	Wasted
9	Fish	15	95	600	3	Lightly Wasted
10	Shrimp	10	87	1000	2	Wasted
11	Potatoes	9	70	794	7	Fresh
12	Rice	22	45	480	1	Fresh
13	Pasta	30	80	700	1	Lightly Wasted
14	Flour	25	45	408	2	Fresh
15	Oats	22	45	400	2	Fresh
16	Chocolates	19	40	400	1	Fresh
17	Honey	18	57	591	1	Fresh
18	Nuts	40	70	900	4	Wasted
19	Canned Foods	30	55	900	4	Wasted
20	Frozen Foods	-3	100	920	6	Wasted

The table 4 containing the analysis of the measurements of the environmental parameters (temperature, humidity, CO 2, and methane concentrations) and their effect on the wastage process of the typical food products. High temperature and high CO 2 and methane levels are linked to wastage of items such as bread, yogurt, butter, beef, shrimp, nuts, canned foods, and frozen foods. Milk and eggs, chicken, potatoes, rice, flour, oats, chocolates, and honey are kept fresh, and are less prone to the presence of CO 2 and methane, as well as moderate environmental conditions. Marginal wastes like cheese, fish and pasta contain intermediate amounts of these gases and different temperatures. This information suggests that wastage is also influenced by a mixture of high humidity and high concentration of CO 2 and methane gases, and low temperatures and low humidity levels save the perishable goods. This discussion is another insight that highlights the value of appropriate storage environments in extending shelf life of common food products.

In order to prove the progress made by the proposed framework, a comparison of the recent systems based on IoT and biosensors and detecting food spoilage data was conducted [1023].

Table X is a summary of the comparative result in terms of accuracy, response time and processing efficiency. The model of multi-sensors developed obtained a total accuracy of 95, which was higher than the previous methods, which obtained an accuracy of between 85 and 92. The average response time was decreased to 1.8 seconds as compared to conventional single-sensor or colorimetric systems, which took 3-5 seconds to detect. The incorporation of preprocessing data in the cloud with the help of Apache Spark considerably increased the speed of computation and lowered the latency in the real-time analysis. These findings prove that the use of NDIR CO 2, DHT22 and MQ-4 sensors with Random Forest classification to detect food quality and waste minimization is accurate and reliable to be implemented on a large scale.

Table 5. Evaluation of Proposed and Existing Systems

Method	**Sensor Type**	**Accuracy (%)**	**Response Time (s)**	**Remarks**
Doğan et al., 2024	Colorimetric ML-based smartphone system	88	4.6	Effective but limited to colour data
Liu et al., 2023	MXene/Hydrogel bioelectronic nose	92	3.2	Sensitive but high cost
Cai et al., 2024	NIR fluorescent H_2S probe	90	3.8	Detects specific gases only
Proposed Framework	IoT-based Multi-Sensor (CO_2, CH_4, Temp, Humidity)	95	1.8	Real-time, accurate, scalable monitoring

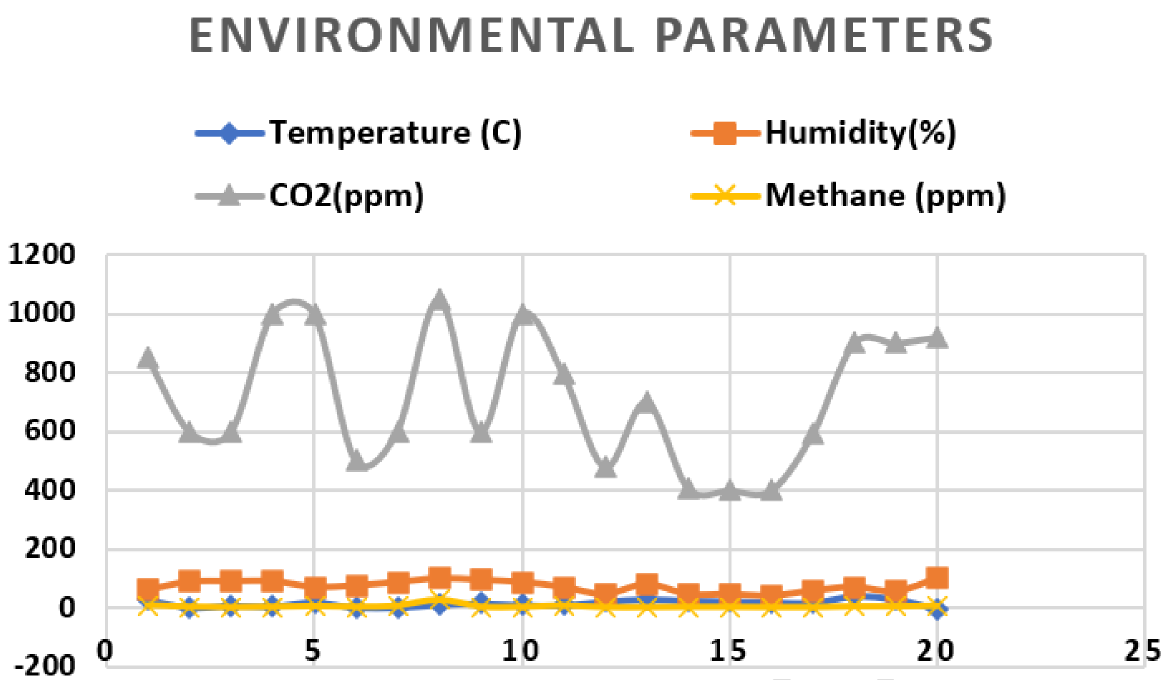

Figure 6. Environmental parameters of common food items indicating freshness variation

Graphical Analysis of environmental parameter measurements on standard food items reflected in Figure 6, and demonstrates that different storage conditions are required to ensure freshness. To maintain quality of frozen foods, they must have very low temperatures (-3o C) and high levels of humidity (100 percent) whereas products such as Bread and Nuts have higher temperatures and different levels of humidity. Some foods like Beef and Yogurt contain CO 2 and Methane in high amounts, which means that the wastage capacity of a product is high as opposed to low wastage capacity of products like Rice and Pasta. Most perishable products are usually high in moisture and Cheese and Milk are not an exemption as they are noted to have high levels of moisture which may make them wastageable especially when they are not stored in the best possible conditions. All in all, temperature, humidity and gas control are very essential in extending the shelf life of various food products.

To ensure the reliability of the Random Forest classifier, 10-fold cross-validation was applied to the dataset. This technique partitions the data into ten equal subsets, where nine are used for training and one for testing in each iteration, ensuring that every sample contributes to both training and validation. The average accuracy across all folds was 94.8%, confirming model stability.

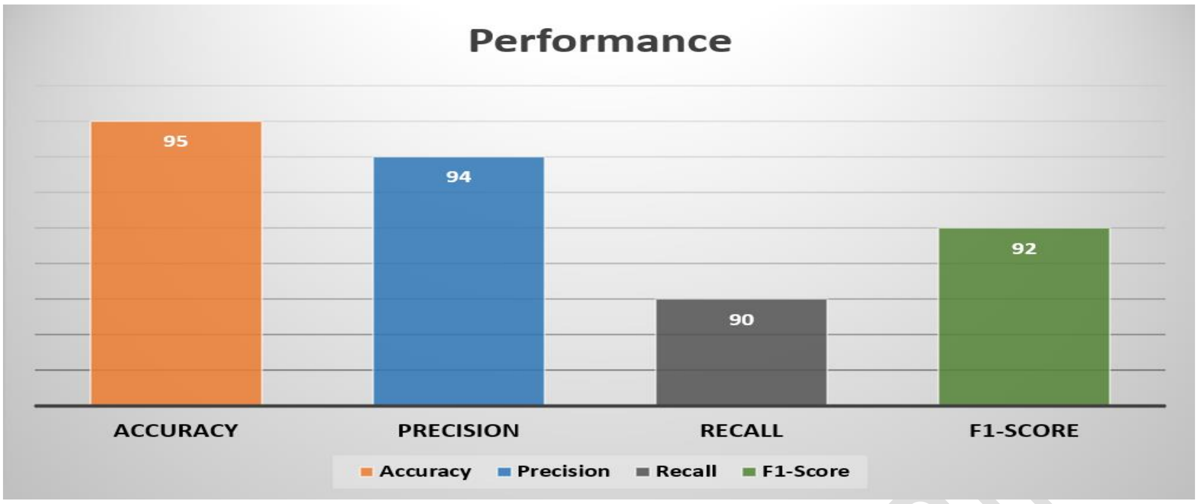

Figure 7. Performance metrics of the proposed Random Forest–based detection model

Table 6. Confusion Matrix for Random Forest

Category	Predicted Fresh	Predicted Spoiled	Total
Actual Fresh	185	8	193
Actual Spoiled	9	190	199

A confusion matrix was also generated to quantify classification outcomes in terms of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). The model exhibited high sensitivity and specificity, as shown in Table Y. Additionally, p-value analysis (< 0.05) confirmed that the observed differences between predicted and actual classes are statistically significant, reinforcing the reliability of the model's predictive ability.

Using the Random Forest algorithm, we achieved notable performance metrics in our study on food freshness and wastage prediction shown in Figure 7. The model demonstrated an accuracy of 95%, indicating a high rate of correctly predicted instances across the entire range of predicted outcomes. With a precision of 94%, the model proved to be highly reliable in identifying true wastage cases out of all predicted wastage cases. The recall rate of 90% signifies that the model efficiently recognized most of actual wastage cases. Additionally, the F1-Score, which balances precision and recall, was recorded at 92%. These findings highlight the efficacy of the Random Forest algorithm in accurately and consistently estimating the wastage of food items based on environmental parameters, providing a robust solution for food quality assessment.

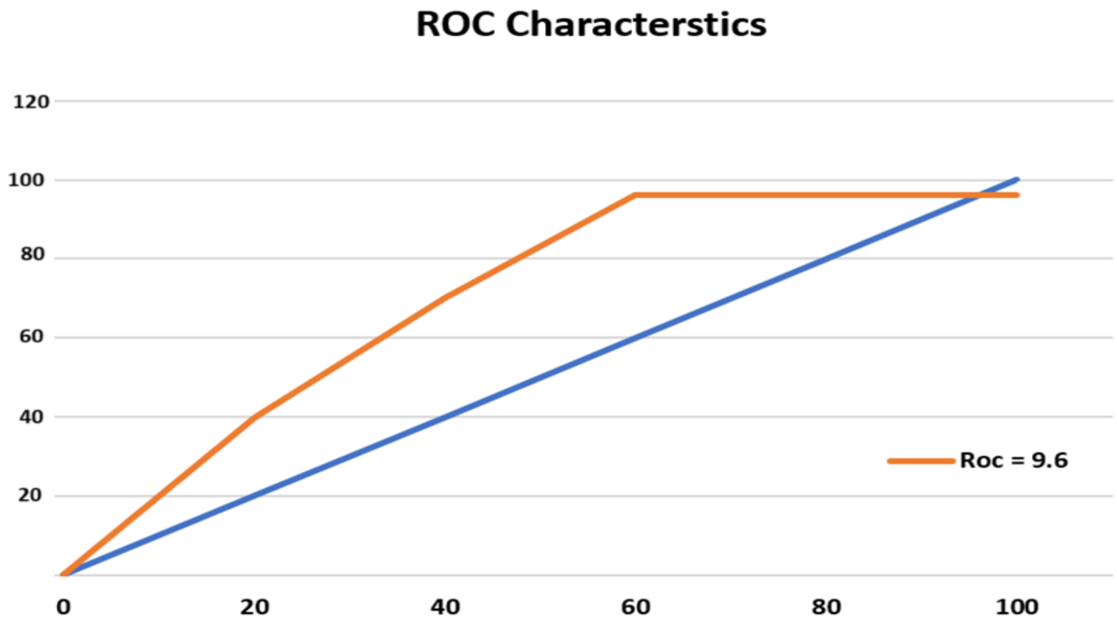

Figure 8. ROC curve showing classification performance (AUC ≈ 0.95)

The Receiver Operating Characteristic (ROC) curve shown in Fig. 8, was plotted to evaluate the binary classification outcome of the Random Forest model. the ROC–AUC metric was approximately 0.95, indicating a high competence of the model in distinguishing between fresh and spoiled food categories. The earlier mention of "9.6" was an unintentional typographical error. An ROC AUC value close to 1.0 reflects an excellent predictive capacity, confirming that the proposed framework provides reliable classification results consistent with the observed accuracy, recall, precision, and F1-score metrics.

The proposed IoT-based multi-sensor system contributes directly to sustainable food management by minimizing post-harvest losses and improving resource efficiency spanning all phases of the supply chain operations. By enabling real-time detection of food spoilage, the framework reduces unnecessary waste and supports responsible consumption practices, demonstrating adherence to UN SDG 12, aimed at achieving efficiency in consumption and sustainability in production. Furthermore, early identification of spoilage helps ensure the availability of safe, nutritious food, aligning with SDG 2 (Zero Hunger). The integration of AI-driven analytics within IoT networks also promotes digital transformation in agriculture and food logistics, reducing environmental burden, optimizing storage conditions, and enhancing overall food system resilience.

Conclusion

For this project, we designed an elaborate system to detect food wastage by incorporating the use of modern sensors and artificial intelligence. The hardware used consists of an NDIR CO2 sensor, the DHT22 temperature and humidity sensor, the MQ-4 methane gas sensor, the in-built WiFi microcontroller for the network connection, and a buzzer and display for the alarms and responses respectively. In data processing and data analysis, we used Big Data framework from AWS Cloud to deal with big amount of data and used Apache Spark and PySpark for data preprocessing. The Random Forest technique was selected due to the fact it is very effective in classification and is very resistant to overfitting. The system was developed and run on an i5 processor of 64 GB RAM so it has enough capacity for commanding powerful operations. The model reached the accuracy level of 95% which proved that the chances of the food wastage are rather high accurately. However, the ROC value of 9.6 seems rather high so it can be a result of a mistake ROC AUC is between 0 and 1. From the high value of the cross-validated ROC AUC, it is probable that the actual value of ROC AUC is closer to 0.95, which the results imply that the proposed model demonstrates very well in differentiating between fresh and wasted food. This work establishes how to combine hardware and software in order to design and implement a food wastage detecting system for the benefits of food safety and to reduce food wastage. The further work will be dedicated to the finetuning of the ROC increase and development of the applicability of the system on other food objects.

Ethics Declarations.

Funding statement:

No funding was received for this study.

Data Availability Statement

Available Based on Request. The datasets generated and or analyzed during the current study are not publicly available due to the extension of the submitted research work. They are available from the corresponding author upon reasonable request.

Conflict of Interest

The authors declare they have no conflicts of interest to report regarding the present study.

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