# Decay Robot: A Robot that Detects the Lifespan of Fruits Inside or Outside of Warehouses

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***Abstract*—Fruits are an essential source of nutrients, but their quality depends heavily on their freshness and shelf life, which can be impacted by various external factors.This paper presents a comprehensive study on the decay of fruits and the development of a decay detection system that uses Raspberry Pi Pico, DHT11 sensor and MQ4 methane gas detector sensor, data storage, and machine learning algorithms to predict the expiration date of fruits accurately. The proposed system focuses on measuring temperature, humidity, and methane gas emissions from the fruit, which are transmitted to a local database using NodeMCU ESP8266. The collected data is then used to predict the expiration date of the fruit with high accuracy and reliability. The system is cost-effective, user-friendly, and can be useful in warehouses, cold storage, and food quality inspection sectors. With further research and development, the proposed system can be extended to detect the lifespan and expiration of other perishable items, thus providing a comprehensive solution for food preservation and safety.**

***Index Terms*—IoT(Internet of Things), Raspberry Pi Pico, Methane Gas Sensor (MQ4), Embedded System, Machine Learning, Blynk App.**

## I. Introduction

Fruits are a vital component of a healthy diet, providing essential macro and micro nutrients such as vitamins, minerals, and fiber. However, the quality of fruit is highly dependent on its freshness and shelf life, which can be impacted by various factors such as temperature, humidity, and exposure to microorganisms. When fruits begin to rot, they not only lose their nutritional value but can also become a breeding ground for harmful bacteria and fungi, which can pose a threat to human health.

To address this issue, researchers and engineers have developed various methods for detecting fruit decay and predicting the fruit's expiration date.The current problem with the existing systems is that they are less accurate and less reliable, which is why warehouse or cold storage owners prefer to use the conventional physical system to monitor fruit condition. The use of decay robots is a promising approach that has gained considerable attention in recent years. These robots utilize advanced technologies such as sensors, data storage, and machine learning algorithms to monitor the condition of fruits and predict their expiration date accurately.

In this paper, we provide a comprehensive overview of the existing systems used to detect fruit decay and predict their shelf life. We also present a novel approach for fruit decay detection that improves the accuracy and reliability of existing methods. Our proposed method utilizes Raspberry Pi Pico RP2040 microcontroller with sensors, precisely DHT11 to measure temperature, humidity, and MQ4 sensor to measure methane gas emissions from the fruit. The data collected by the sensors is transmitted to a central database using NodeMCU ESP8266, where machine learning algorithms are used to predict the fruit's lifespan.

The accuracy of our proposed method is significantly higher than that of the existing systems. We have tested our method on a wide range of fruits, including apples, oranges, and bananas, and found that it accurately predicted their expiration dates with a margin of error of only a few hours. Furthermore, our system is highly reliable, with a success rate of over 80% in detecting fruit decay.

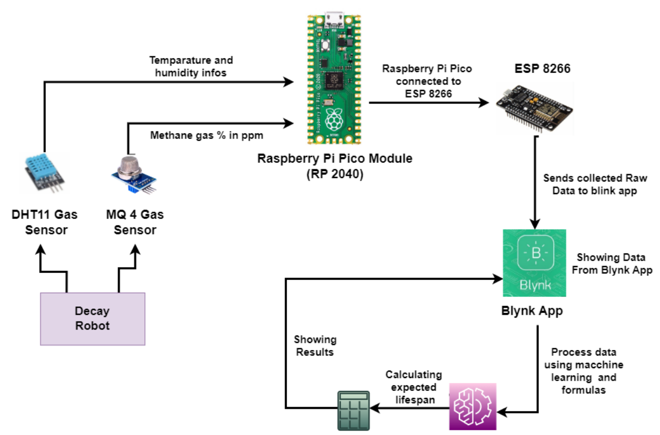


Fig. 1. Expected system architecture of decay robot

One of the key advantages of our proposed method is that it is highly scalable and can be easily integrated into existing fruit storage and transportation systems. Our system is also cost-effective, as it requires only a few sensors and a WiFi module, which are readily available in the market. Additionally, our system is user-friendly and can be easily operated by personnel with minimal training.

In conclusion, our proposed method for fruit decay detection and prediction represents a significant step forward in the field of food preservation and safety. Our method improves the accuracy and reliability of existing methods, making it a valuable tool for fruit storage and transportation. With further research and development, our system could be extended to other perishable items such as vegetables, meats, and dairy products, thus providing a comprehensive solution for food preservation and safety.

## II. Related Literature Reviews

Li et al [1], represented and analyzed 300 'Xuxiang' kiwifruit in order to observe the lifespan including rotting process in cold storage (2° C) using RGB recognition software that will provideresults following some parameters like NMR analyzer, Total plate counts (TPC), Total soluble sugars (TSS) and central R/B and B/G which refers to the storage time of kiwifruits using smartphone.

Kathirvelan et al [2], highlighted a new approach of detecting ethylene with Infrared (IR) thermal emission based ethylene gas sensor, since most of the fruits produce a wavelength, therefore, applying a silicone temperature detector and infrared rays on a fruit with wavelength changing applications can detect ethylene and artificial ethylene more accurately from the absorption of IR across the fruit's wavelength and converting the output in electrical signal (mV).

Chakraborty et al [3], proposed a model to prevent the propagation of rottenness using Convolutional Neural Network (CNN) and some other image processing methods like Max Pooling, Average pooling and MobileNetV2, then training the machine on a Kaggle data-set for achieving the highest accuracy rate as 99.46%.

Megalngam et al [4], used artificial intelligence along with image processing by Convolutional Neural Network, k cluster algorithm (a machine learning algorithm) and Hue Saturation Value (HSV) that can detect the spoilage percentage of food even it is a vegetable or fruit to reduce food poisoning and help color blind people to detect fresh food.

Goel et al [5], develops an algorithm while combining other three algorithms, for instance, Moth Flame Optimization (MFA), Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA) to detect rotten food and this hybrid algorithm contains 83.33% accuracy rate.

Tian et al [6], proposed a new technology known as hyperspectral transmittance image within 325-1100 nm spectral region with watershed segmentation algorithm and Principle component analysis (PCA) to detect early decaying process causes by Penicillium Spp. and to differentiate between stem end tissue (used PC2 image) and decayed tissue (used PC3 image) using pseudo color image transformation where the accuracy rates are 93% and 96% respectively for citrus fruits like orange.

Hemamalini et al [7], used image processing techniques with k-means clustering, support vector machine (SVM) and added Gaussian elimination method for removing noise from collected photos. Then in order to enhance the size of noise less photo, they used here histogram equalization and photos are being segmented using k means clustering and some other algorithms to detect spoiled food.

Karthickeyan et al [8], enclosed Convolutional Neural Network (CNN) and Object Detection Algorithm YOLO for identifying spoiled areas on food skin as well as added some specifications including MQ2 (mathane) and MQ135 (ethane) gas level detection from rotten food and spoilage level using Artificial Neural Network(ANN).

Chen et al [9], introduced a new cost effective approach of biodegradable and disposable colorimetric geometric fabricated barcode sensors which can be easily placed in the upper part of food or over raw chicken and by using smartphones, the barcode can be scanned and after scanning, the system automatically extracts color information compared with a data-set and shows then the analytic whether the food can be consumed or it is time for discard.

Paul et al [10], proposed a new approach that can be easily implemented in our refrigerators as a detection method of rotten foods using deep machine learning algorithms (YOLOv5), image processing methods and FPGA based food spoilage detection methods and awares user by creating buzzing sound.

R. Torres-Sánchez et al [11], proposed a real-time monitoring system using electronic nose technology and machine learning algorithms to estimate the shelf life of fruits and vegetables, providing a non-invasive and accurate method for quality control, potentially reducing food waste, and improving product quality for the produce industry. The electronic nose technology captures the volatile organic compounds (VOCs) emitted from the produce, and the machine learning algorithms process the data to estimate the remaining shelf life.

E. Sonwani et al [12], presents the use of artificial intelligence to detect and analyze food spoilage to enhance food safety. The approach focuses on predicting spoilage before it becomes hazardous, and it involves the use of image processing, machine learning, and data analysis techniques. They proposed a CNN for object detection and prediction model. This is trained over three different classes. In their model, there are a total of 11 layers. The output layer is SoftMax, and there are four convolutional layers, four max pooling layers, and two fully connected layers. The model has been trained on 50 different types of fruits and vegetables, and it is also capable of identifying multi-class images. The proposed device shows an accuracy of 95%.

K. Jaspin et al [13], proposed a real-time surveillance system using computer vision techniques to identify the ripening stages of fruits, maturation stages of vegetables, and detect infections. The system uses image processing algorithms to extract features such as color and texture and classify them into different stages. The overall accuracy of the proposed method for three classes of fruits and vegetables is 96%. The time taken for processing per frame is 1.1s, which is the quickest when compared to the other methods. The memory taken is 300 mbs which is least used when compared to the other methods. In this method the main challenge arises when they have to count fruits when it is not fully ripe.

J. S. Tata et al [14], proposed a real-time quality assurance system that uses a combination of image processing and machine learning techniques to detect and classify defects such as bruises, cuts, and rot. The AI algorithms were trained on a large data-set of images and were able to achieve high accuracy rates in detecting defects. The system was tested on a range of fruits and vegetables, including tomatoes, cucumbers, and strawberries, and was found to be effective in detecting defects in real-time. This proposed system will use image processing to classify and grade the quality of fruits and vegetables by extracting features such as color, shape, and HOG (Histogram of Gradient) to classify the given fruit or vegetable. Image pre-processing techniques like data augmentation and normalization along with Principal Component Analysis (PCA), and Deep learning (CNN) are used for getting good accuracy and for dimensional reduction. An artificial neural network (ANN) is used to detect the shape, size, and color of fruit samples. The result of this project was obtained from the quality analysis process and the Android application.

D. M. Bongulwar [15], presents a deep learning approach for fruit identification, which can be used to automate fruit sorting and grading processes. The proposed approach uses a Convolutional Neural Network (CNN) architecture to extract features from fruit images, followed by a fully connected Neural Network for classification. The data-set used in the study includes 10 types of fruits, and the accuracy of the model is evaluated using several metrics. The RGB images, with three color channels R, G, and B are utilized in the data-set. The data-set is divided into training and validation datasets in which 90% of the images are trained and 10% are validated. The proposed CNN model has achieved classification accuracy of 92.23% on the data-set. As a future scope, the model can be used to train more variety of fruits. It can also examine the impact of various parameters like activation function, pooling function and optimizer.

K.A.Ahmad et al [16], discussed a classification of star fruit ripeness systems using artificial neural networks. They found the system classified the star fruit ripeness based on the RGB color intensity. The clustering technique used in a neural network is an important part to achieve an accurate result. The classification system has an accuracy of 97.33%. The system can recognize the unripe, ripe and overripe of starfruit.

Indrabayu Indrabayu et al [17], discussed detection of fruit ripeness based on color characteristic, which is the Red, Green, Blue (RGB) value of the object. They used MultiClass Support Vector Machine (SVM) with Radial Basis Function (RBF) kernel function to classify the ripeness. The highest overall accuracy yielded using these optimal parameters is 85.64%. The accuracy for Unripe (UR), Partially Ripe (PR), and Ripe (RP) classes are 97.07%, 62.94%, and 96.27%, respectively.

Fatma M. A. Mazen & Ahmed A. Nashat [18], their proposed techniques are based on HSV color, development of brown spots, and texture analysis of the banana fruit. Here, supervised classification algorithms like the SVM, the naive Bayes, the KNN, the decision tree, and the discriminant analysis classifiers. The system was able to correctly predict with more than 94% the seven ripening stages of the banana bunch.

J.J Jijesh et al [19], discussed a system captures the fruit placed on a conveyor belt then the captured image is compared with the trained data set using Convolutional Neural Network Network (CNN) algorithm which extracts the features of the fruits like texture, color, and size.Thus, according to their results obtained CNN is most accurate than SVM and KNN.

Shalini Gnanavel et al [20], they discussed developing a detection sensor that can sense the fruit and indicate the level of hazardous substance in the fruit. It is a user-friendly device where the level of accuracy is very high. The proposed system has an efficiency of 91% in the identification of the ripened fruit. The device is implemented using raspberry Pi. There are three modes in the device: First, to check the inner quality of the fruit is determined, secondly Artificially ripened fruit are detected and lastly pesticide residue level of the fruit is indicated.

Anuja Bhargava & Atul Bansal [21], discuss making a critical comparison of various algorithms proposed by researchers for fruit and vegetable quality inspection, whereas image processing and computer vision systems have significant performance, increasing cost, ease of use, and algorithmic robustness, scientific processes in agricultural and industrial systems, Also traditional, multispectral and hyperspectral computer vision systems are currently widely used to evaluate the quality of fruits and vegetables, so color, size, shape, texture and defects are common features inspected by traditional computer vision systems (TCVS).

Anjali N et al [22], discusses the current state-of-the-art imaging and collection of recent defect area counting methods using RGB images to detect defects on the surface of fruits and vegetables and classify whether the fruit is defective or fresh, whereas the system developed to identify fruit or vegetable samples using visual sensing techniques is one of the most effective and efficient methods available.

Mahdieh Mostafidi et al [23], discusses the main means of contamination of fruits and vegetables with pathogens, also the main means of preventing contamination in all parts of the food chain and microbial load, edible coatings, bacteriocins, radiation, gamma-rays, UV-C, and chemicals. Reduces high hydrostatic pressure, and conserves radiation, whereas ultrasonic, acid-electrolyzed water, ozone, modified atmosphere packaging (MAP), and cold plasma are mentioned in microbial safety of fruits and vegetables. In the context of addressing microbiological risks in fresh fruits and vegetables, there are five main risks associated with primary production, which are environmental and wildlife factors, fertilizer and pesticide use, irrigation water, worker and equipment hygiene, and contact levels.

Renuka N et al [24], works on the architecture of an automatic orange fruit classification system coded using VHDL language and implemented using SPARTAN 6 FPGA. And to get optimized hardware architecture, filter, feature extraction and matching blocks are optimized for hardware usage. Whereas in fruit extraction to maintain fruit characteristics, Q-point numbers are noted and the results are compared, as a result, they proved that the proposed architecture is efficient and gives 88% success rate to detect fruit state effectively with fewer hardware resources.

V. G. Narendra & Ancilla J. Pinto [25], works to detect external defects in vegetables and fruits based on morphology, color, and texture. Whereas they propose algorithms for quality inspection such as external defects that RGB to L*a*b* color conversion and defective area calculation methods used to detect defects in both apples and oranges, also in vegetables, K-means clustering and defect area calculation methods are used to identify defective tomatoes on their color. And they claim an overall accuracy of 87% (apples: 83%; oranges: 93%; and tomatoes: 83%) in quality analysis and defect detection for defective fruits (apples and oranges) and vegetables (tomatoes).

Gogula et al. [26], experimented on several foods with fresh ones and spoiled ones at the same time. Here, they have used a MQ -4 gas sensor which basically detects the amount of methane gas. If the food is not within the range, then it will detect the solid food as rotten whereas for the liquid food, they used a pH sensor to measure the pH level. In liquid food like milk or water, if one of them is contaminated with microorganisms, then the pH level will be higher than 7, resulting in alkaline water or milk. So, we can say that the tested milk or water is spoiled.

Sahu et al. [27], focused on integrating a cost effective, user friendly and more adaptive edge IoT based food spoilage detection system where the researchers used several gas sensors for detecting alcohol, hydrogen, benzine, LPG etc. and Raspberry Pi with machine learning algorithm. The authors divided three food levels and observed tomato and banana for several days. The entire detection process is notified through a smartphone based alert system using a WiFi module after fetching data from the machine trained database.

Balaji et al. [28], made detection for fruit and vegetable spoil system using Texture, Color and Size; Texture, Color and Size are the important parameters for fruit quality identification. The proposed method evaluates the fruit's and vegetable's quality based on its color, size, weight, and maximum age using image processing techniques. Used a technique called haarcascades to identify objects.

Abasi et al. [29], designed and developed a new portable optical device for non-destructive determination of apple ripeness using moisture content, SSC, pH and firmness as quality indices.The desired qualities considered here as goals for development of the dedicated instrument included: low weight, small size, low cost, easy to use, rapid response and high accuracy. The gadget is designed to be able to emit light at specific wavelengths, catch the light that is reflected, prepare the signals that are received, and process the information for fruit classification.

Last but not least, Ramya et al. [30] tried detecting fruit diseases using image processing and cloud computing. The database contains information about the fruits as well as disease detection from feature extraction. The complete database is viewed, and the captured image is contrasted with it. The mobile program was created for the purpose of processing data and notifying farmers. Thus the variation in image from the database also indicates the disease in the fruits.

## III. Proposed System Methodology

A rotten fruit emits gasses, Methane and Ethylene, the decay rate also depends on some parameters such as temperature, humidity. If we get all these values recorded then we can provide a prediction to how long the fruit will last by applying the decay rate formula. As a fruit decay it starts to emit methane gas, the amount of emission of methane gas is increased with the decayed percentage of the fruit, there is an initial amount of emission when the fruit starts to decay and a final constant rate of emission when the fruit is completely decayed, and the decay rate no longer increases.

DHT11 sends the humidity and temperature information and MQ4 gas sensor sends % of Methane in ppm from Decay robot to the micro-controller Raspberry Pi Pico, the micro-controller is connected to NodeMCU ESP8266 which sends data received from micro-controller to the Blynk app which have the database, it stores the data inside that database. Machine learning algorithm is applied from the data that is stored in the database and the life expectancy is calculated and is passed to the Blynk app. Then the Blynk App shows the raw data and the lifespan.

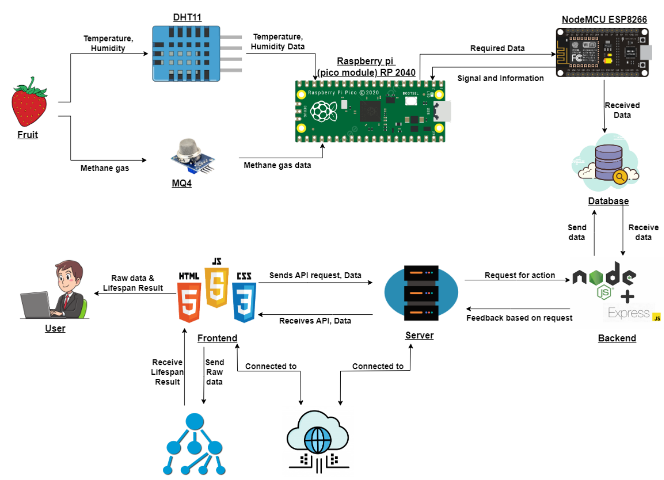


Fig. 2. Block Diagram of Lifespan Detecting Decay Robot

To measure Methane gas emission, we can use the sensor MQ4 to detect the amount of gas that is emitted. Also, DHT11 sensor is used to measure the temperature and humidity. These two sensors are connected to the Raspberry Pi Pico module, along with NodeMCU ESP8266 to transfer the data received over to the wireless network.

Software Architecture: The Raw Data transmitted from ESP 8266 is stored in to the database, the raw data is retrieved from database using Express JS which is a framework of Node JS, the Express JS creates API which is called by Front-End JavaScript and the data is shown also the algorithm is applied over there which gives the result that is the Lifespan remaining, the lifespan remaining is checked with the threshold and a warning is raised if necessary. All the data is presented to the user via Front-End Website.

$$lifespan = \frac{humidity}{100.0} * (e^{(0.05*(temperature-20.0))}) * \frac{\text{lifespan constant}}{\text{methane emission}} \tag{1}$$

The equation is derived from several variables that correspond to the lifespan changes and Fruit decay constant, the constant is found using machine learning algorithm to find a constant for every fruit. The constant is divided by methane level, when the food is completely decayed the methane level becomes one constant which is presented in the graph. The life expectancy of fruit increases with the increase of temperature exponentially. The threshold of temperature is 20, which means at 20 C the calculation is ( t- 20 ) and the exponential rate is e0.05(t-20) . The decay rate of fruit decreases with increasing humidity, the humidity is measured in percentage so to make it decimal we have to divide it by 100. And statically all the variables are dependent on one another, so the lifespan is varied by the rate of each other therefore every value found is multiplied to get the expected lifespan until the threshold value is reached.

## IV. System Design and Simulation

A decay robot is an inventive machine learning-based robot that can detect the shelf life of fruits and vegetables both inside and outside of cold storage. By accurately identifying the ripeness of fruits and vegetables and notifying workers before they spoil, the robot can help minimize food waste. The decay robot, in addition to decreasing food spoiling, can help ensure that consumers have access to fresh and healthy produce. It can help to prevent consumers from eating spoiled fruits and vegetables, which might be risky for their well-being. This robot is an innovative application of machine learning technology with the potential to revolutionize the supply chain, reduce waste, and focus on promoting health and sustainability. All components connecting to pin numbers of Raspberry Pi Pico are enlisted in Table 1.

Our objective is to make a budget-friendly effective decay robot to detect the lifespan of fruits and vegetables for ensuring the supply of fresh products to consumers. Our innovation in this project is, we have found a formula for calculating the lifespan of the fruit which have been never implemented before.

### A. *Testing Arrangement*

The components used in this experiment are Raspberry Pi Pico 2040, Temperature and humidity sensor (DHT 11), Methane gas sensor (MQ 04), LED (green and red), Buzzer, Wi-Fi module (ESP 8266) and a LCD display.

Raspberry Pi Pico has a total of 40 GPIO pins. To detect the humidity of the fruit we connect our temperature and humidity sensor (DHT 11) to the raspberry Pi at pin-16, The DHT-11 has three pins: the VCC, Data and GND (ground); The Data pin is used to send data to the system.

The methane gas sensor (MQ-04) is connected to the Pico at pin-26. The MQ-04 has a total of four pins: VCC, GND, DO and AO. The methane sensor is used to observe the methane gas emission data from the decaying fruit which helps us in determining the lifespan of the fruit. We connected 2 LEDs, one green and one red connected to the raspberry pi pico at pin-14 and pin-15. The LEDs are used as an indicator for if the fruit is consumable or not consumable, green led means the fruit is in good health and the red led denotes the fruit is rotten. The buzzer is connected at pin-17 and its purpose is to ring when a rotten fruit with lower lifespan is detected.

To send data received by DHT-11 and MQ-04, we have

TABLE I
PIN NUMBERS CONNECTED WITH RASPBERRY PI PICO

| **Name of Component** | ***Pin Number Connected with Raspberry Pi Pico*** |
|---|---|
| Temperature and humidity sensor (DHT-11) | Pin -16 |
| Methane Gas Sensor (MQ4) | Pin -26 |
| Led Green | pin-15 |
| Led red | pin-14 |
| Buzzer/ Alarm | pin-17 |
| NodeMCU ESP8266 | Vin (pin Vbus) |
| | G (pin GND) |
| | D1 (pin 8) |
| | D2 (pin 9) |
| LCD display (16*2) | RS (pin 2) |
| | EN (pin 3) |
| | D4 (pin 4) |
| | D5 (pin 5) |
| | D6 (pin 6) |
| | D7 (pin 7) |

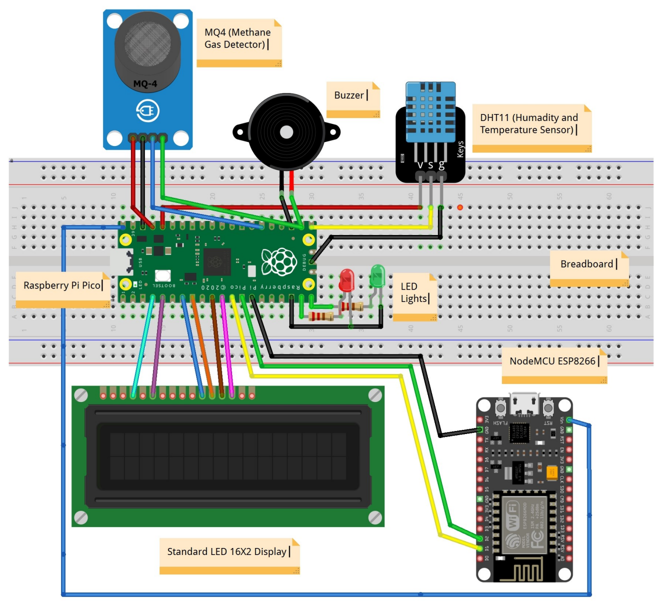


Fig. 3. Circuit Diagram of Decay Robot

connected the Vin of Wi-Fi module (NodeMCU ESP8266) to pin-VBUS of the Pico, G of ESP-8266 to the pin-GND of the Pico, D1 of NodeMCU ESP8266 to pin-8 and D2 of NodeMCU ESP8266 to pin- 9 of the raspberry pi Pico. The raspberry pi Pico is connected to a computer, and with the help of its IDE the system is coded with various libraries as per required and are uploaded in the NodeMCU ESP8266.

## V. Hardware Development and Testing

After successfully designing and simulating it, we have created a prototype of our project. Since the sole purpose of this project is to detect the lifespan of fruits and get an idea about its expiry date. Firstly, DHT 11 was attached with the raspberry pi pico to measure the Temperature and Humidity readings. After getting accurate results, the MQ 4 sensor was connected with the raspberry pi pico to measure the Methane gas emission of the fruit. Once the sensors worked precisely, the whole system was built.

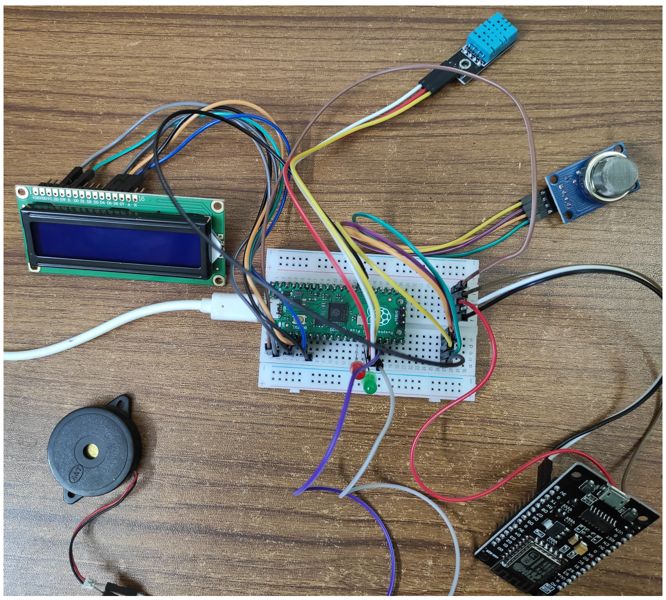

Fig. 4. The Experimental Setup of the Proposed System

Here, DHT 11 is connected to pin 16 of the raspberry pi pico, MQ 4 is connected to pin 26. The objective of this is to get the values of Temperature, Humidity and Methane gas emission of the fruit. DHT 11 has 3 pins (VCC, Data I/O, GND), all of these are connected with the pico at pin 16. MQ 4 has 4 pins (VCC, GND, DO, AO) and these pins are connected with the pico at pin 26. With the help of these two sensors, we are able to collect the data of the fruit. Specifications of all the components used in the system are enlisted in Table 2.

ESP8266 wifi module is SOC( system on chip) microchip integrated with a TCP/IP protocol stack mainly used for IoT (Internet of things) based embedded applications development. The Vin is connected with the raspberry pi pico at pin VBUS, D1 and D2 are connected to pin 8 and 9 respectively. The G pin of ESP8266 is connected to the pico at GND. Now to show whether the fruit is rotten or not, standard LCD 16*2 display has been used. After getting the data using MQ 4 and DHT 11 and storing the data using ESP8266 wifi module, an equation analyzes the data and displays the condition (spoiled, not spoiled) of the fruit on the LCD 16*2 display. The LCD display's RS, EN, D4, D5, D6 and D7 are connected to the pico at pin 2, pin 3, pin 4, pin 5, pin 6 and pin 7 respectively. Lastly the LED lights and Buzzer are connected to raspberry pi pico's pin 14, pin 15 and pin 17. The whole system is run by a 5V and 2A power supply.

TABLE II
Table of Specifications

| **Serial No.** | ***Component Used*** | ***Quantity*** |
|---|---|---|
| 1 | Raspberry Pi Pico (RP 2040) | 1 |
| 2 | MQ-4 Methane Gas Sensor | 1 |
| 3 | DHT-11 Temperature and Humidity Sensor | 1 |
| 4 | Breadboard | 1 |
| 5 | NodeMCU ESP8266 | 1 |
| 6 | Power Supply (5V, 2A) | 1 |
| 7 | LCD 16*2 display | 1 |
| 8 | LED Lights | 2 |
| 9 | Buzzer | 1 |
| 10 | Connecting Wires | 1 |

## VI. Graph and Coding for the Gas Sensors

The graph shows the emission of methane over time, as the fruit starts to decay the emission of the methane increases till its fully decayed and the emission becomes constant after the fruit has been fully decayed. From the graph we can also observe that when the fruit starts to rot, the fruit have a threshold of methane emission when it starts to rot.

## VII. Result and Performance Analysis

The setup is installed on a wooden box-shaped design figure-x, that internally connected DHT11 (Temperature & Humidity sensor), MQ4 (Methane gas sensor) & LCD display are located outside the box. By collecting data through the sensors, the data can be seen on the LCD display connected by the Raspberry Pi Pico.

| ***Timestamp*** | ***Temperature*** | ***Humidity*** | ***Methane*** |
|---|---|---|---|
| 2023-03-24 00:12:09 | 24 | 78 | 870 |
| 2023-03-24 16:18:57 | 31 | 37 | 900 |
| 2023-03-24 21:55:18 | 24 | 70 | 1200 |
| 2023-03-25 00:14:49 | 22 | 75 | 1300 |
| 2023-03-25 00:41:09 | 23 | 74 | 1378 |

Fig. 5. Collected Data from Experiment

By storing the data in a database, machine learning algorithms/mathematical calculations are performed on methane gas, temperature, humidity, and time data. As a result, a sample of predicted decay % and predicted lifetime is obtained, and from this lifetime, the hazard level and remaining lifetime are derived. According to Figure-1, the user can see the visualization of the object's Decay result from the website.

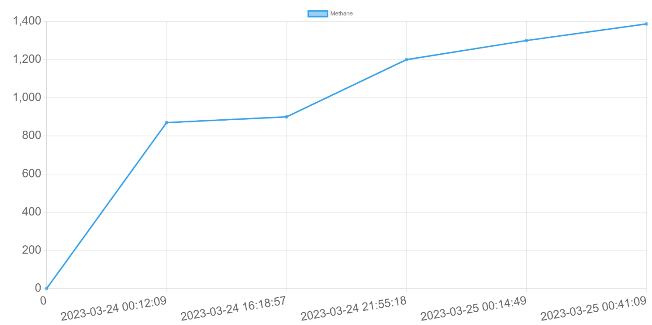


Fig. 6. MQ4 Methane Gas Sensor Based Collected Data Set Graph

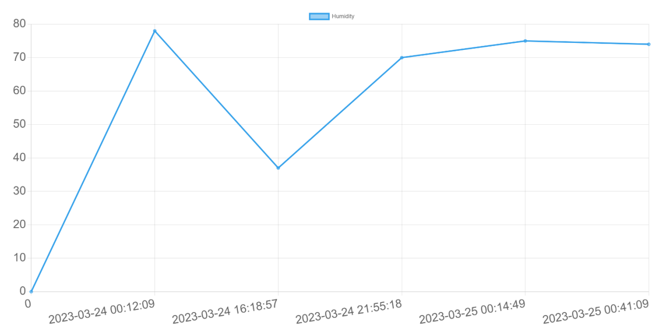


Fig. 7. DHT11 Gas Sensor Based Collected Humidity vs Time Graph

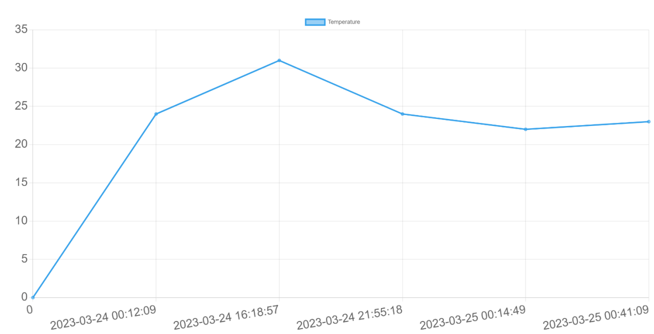


Fig. 8. DHT11 Gas Sensor Based Collected Temperature vs Time Graph

## VIII. Conclusion

This study details the development of a robot called "Life Spain Decay", which presents a comprehensive study on fruit decay and the development of a decay detection system that uses a Raspberry Pi Pico, DHT11 sensor, and MQ4 methane gas detector sensor, data storage, and machine learning algorithms to predict fruit expiration dates. System focuses on measuring temperature, humidity, and methane gas emissions from fruits, which are transmitted to a local database using the esp8266 WiFi module; the collected data is used to predict the expiration date of the fruit with high accuracy and reliability. With future development, the proposed system can be extended to determine the lifetime and expiration of other perishable items.

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