Ethylene gas-based fruit expiry predictor: a sustainable solution to fruit wastage

Olabode Idowu-Bismark[1], Anyiam Chinemere Eberchukwu[2], Oluwadamilola Oshin[1], Ibiang Emmanuel[2], Tonwe Mary[2], Emmanuel Adetiba[1,3]
[1]Department of Electrical and Information Engineering, College of Engineering and Covenant Applied Informatics and Communication African Centre of Excellence, Covenant University, Ota, Nigeria
[2]Department Electrical and Information Engineering, College of Engineering, Covenant University, Ota, Nigeria
[3]HRA, Institute for Systems Science, Durban University of Technology, Durban, South Africa

Article Info

Article history:

Received Dec 31, 2024
Revised Dec 19, 2025
Accepted Feb 22, 2026

Keywords:

Ethylene
Food wastage
Fruit expiry predictor
Fruit grade prediction
Fruit wastage

ABSTRACT

Globally, environmental and economic issues are very apparent regarding food wastage. Fruits play a significant role since they can be damaged easily. Ethylene gas is one of the significant gases produced by fruits when they begin to ripen; it tests whether the fruit is ripe or else spoilable. This work presents a sustainable solution for fruit wastage: an ethylene gas-based fruit expiry predictor (FEP). The system is designed and developed around advanced sensing and artificial intelligence (AI) models for real-time monitoring of ethylene levels and temperature in forecasting the spoilage of fruits. The system consists of non-invasive sensors for detecting ethylene and temperature, a data processing microcontroller, and an AI model trained on a large dataset to make accurate predictions regarding the expiry of fruit. The AI model processes the information collected by the sensors and then displays the grade (level of ripeness of the fruit) on a liquid crystal display (LCD) screen. This solution improves fruit management with reduced wastage in line with international sustainability targets. These would enable real-time and highly accurate predictions of fruit spoilage, allowing end-users informed choices that will eventually lead to reducing the carbon footprint from food waste and increasing food security.

Corresponding Author:

Oluwadamilola Oshin
Department of Electrical and Information Engineering
College of Engineering and Covenant Applied Informatics and Communication African Centre of Excellence, Covenant University
Ota, Nigeria
Email: Damilola.oshin@covenantuniversity.edu.ng

1. INTRODUCTION

The problem of food waste, particularly from fruits and vegetables, has become a major global challenge in recent years [1], [2], with substantial consequences for the environment, economy, and society. As the global population is on an upward trajectory, projected to reach 9.7 billion by 2050 [3], the imperative for sustainable and efficient food production and consumption practices is more pressing than ever. Fruits and vegetables, which constitute over 46% of total food waste [4], are at the forefront of this issue. Central to understanding and mitigating fruit waste is the biochemistry of fruit ripening, particularly the role of ethylene - a natural plant hormone instrumental in the ripening process. Ethylene not only influences the shelf life and quality of produce but also presents opportunities for innovative waste reduction strategies. Ethylene is an important regulator controlling ripening in climacteric fruits [5]. One of the most significant markers of fruit ripening is a color change. The primary cause of the various fruit colors in many climacteric fruits is the build-up of either anthocyanins or carotenoids, which are known to be controlled by ethylene, and the loss of chlorophyll. Tomatoes' green-to-red color change is linked to the breakdown of chlorophyll and the build-up of carotenoids [5]. Other markers are fruit softening, and fruit flavor [5]. The current techniques for ethylene detection in plants were disclosed by Cristescu *et al.* [6]. They include electrochemical sensors, electro-catalytic sensors, gas chromatography, and photoacoustic spectroscopy. These techniques provide an outline of the options available for measuring ethylene in a lab setting [7]. Fruit ripening involves several biochemical processes, which include changes in color, sugar content, acidity levels, texture, and the release of volatile aromas. These changes are vital in shaping the sensory characteristics of the fruit [8]. In the ripening of fruits, non-climacteric and climacteric fruit ripening are the two divisions of the classification. This classification is predicated on the correlation between a visible peak in ethylene emission and an increase in respiration rates during the ripening phase [9].

Artificial intelligence (AI) has been applied in various areas of research, including dynamic spectrum access in television white space (TVWS) [10], and has recently become crucial in predicting fruit ripening, enhancing agricultural practices, and promoting waste reduction. By leveraging advanced algorithms, AI models can analyse various factors that influence fruit ripening and provide accurate predictions. Statistical, machine learning-based (ML-based), and deep learning-based (DL-based) are the primary categories of approaches. Under the statistical and ML-based technique, the color of fruits was used by the authors of [11] to classify fruit ripeness using the Commission Internationale de l'éclairage l*a*b* (CIELAB) color space to distinguish between seven different banana ripeness categories that subject matter experts had previously assigned labels. However, this method may struggle to differentiate between very similar colour shades during intermediate stages of ripening, where colour changes can be subtle. Also, human colour perception varies, meaning what appears to be the same colour to one person may differ slightly for another, potentially impacting the accuracy of CIELAB-based classifications. AI has also been used in other classifications, such as class attendance system using facial recognition [12].

Baietto and Wilson [13] investigates the current and potential applications of electronic-nose devices (with specialized sensor arrays) in the fruit ripeness classification domain. Even though several types of fruit share some olfactory features, each fruit has its aroma, and this may negatively impact the accuracy of the system. In a seminal effort [14] assessed the stage of ripeness of bananas by smelling the fragrant volatiles released by the fruit. For this objective, they developed an electronic artificial nose system in tandem with a pattern recognition engine. It was discovered that the algorithm produced a promising result, classifying bananas with 90% accuracy. In the work of, [15] an optical chlorophyll-sensing system to measure the amount of chlorophyll in bananas as the fruit ripens was developed. The findings of the investigation conducted by [16] indicate that utilizing spectral scattering from either all wavelengths or specific wavelengths can yield more precise forecasts of apple ripening compared to relying on secondary characteristics such as spectral absorption. Aherwadi *et al.* [17] examined the development of fruit maturation categorization and quality detection models utilizing deep learning approaches, specifically convolutional neural networks (CNN) and AlexNet. Using two DL-based CNN models that they constructed, Vijayalakshmi and Peter [18] achieved 98.3±0.8% accuracy for rotten banana recognition and 93.4±0.8% accuracy for classification. The second model they developed performed well.

Chakraborty *et al*. [19] suggested a CNN with five layers, including a convolution layer, a pooling layer, and a fully linked layer, to classify bananas. Using the MobileNetV2 technique, another model that the authors of [19] developed achieved 99.46% accuracy on the training set and 99.61% accuracy on the validation set. The training and validation accuracy of max pooling and average pooling were 94.49% and 93.06%, respectively, and 94.97% and 93.72%, respectively. An independent dataset of 300 apples was used to evaluate the suggested model, and Li *et al*. [20] reported that it performed with an accuracy of 99% for training, 98.8% for validation, and 95.33% overall. Iqbal and Hakim [21] presented an automatic model for sorting and grading mangos using a DL approach, taking into account eight different types of harvested mango attributes, including size, shape, color, and texture. Various data augmentation techniques are employed, including image rotation, translation, sharing, zooming, and horizontal flip. Using enhanced data, the Inception v3 CNN architecture scored 99.2% accuracy for sorting and 96.7% average accuracy for grading when compared to the VGG16, ResNet152, and Inception v3 approaches.

To classify the mulberry fruits according to their level of ripening, a computer-vision program was created and evaluated utilizing CNN [22]. To decrease training costs and increase accuracy, the CNN classification model was refined through the use of transfer learning. Testing was done using a variety of CNN models, including Inception-v3, AlexNet, ResNet18, ResNet50, and DenseNet. For the maturity classification of white and black mulberries, AlexNet, and ResNet18 had the highest accuracy of 98.32% and 98.65%. ResNet18 achieved a total accuracy of 98.03% in classifying genotype and maturity from 600 fruit photos. The CNN algorithm was utilized by Saragih and Emanuel [23] to categorize bananas into four categories: unripe, medium ripe, overripe, and yellowish green. Mangoes were identified by Naik *et al*. [24] using linear classifiers such as k-nearest neighbors (KNN), support vector machine (SVM), and a multilayer perceptron neural network (MLP) after they built their dataset. A system for classifying palm fruit was published by Septiarini *et al.* [25] who created a model to distinguish between three maturity classes: unripe, under-ripe, and ripened. Using sensors and an advanced AI model.

In this work, an ethylene gas-based fruit expiry predictor was constructed, which relies on these fundamental understandings to monitor ethylene levels in real-time and produce the dataset used by the embedded models to predict the ripeness of the various fruits. The contribution of this work is the design and production of the fruit expiry predictor (FEP), which provides real-time monitoring, and the models, which provide higher accuracy of prediction than in earlier works. Also, this work contributes to achieving a decrease in fruit wastage and assists in the achievement of sustainable development goals (SDG) 13, climate action, thus offering users the ability to make empowered decisions [26], [27].

2. METHOD

This section provides a detailed description of the proposed FEP. It describes the system specifications and the various components used in designing the project. It also discusses the various steps involved in implementing the project. Figure 1 is the block diagram of system analysis and design.

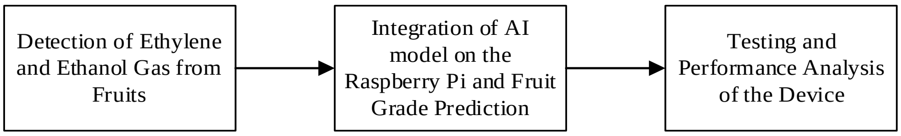


Figure 1. Block diagram of system analysis and design

2.1. Detection of ethylene and ethanol gas from fruits

The FEP houses sensors like the MQ-3 and Winsen C_2H_4, allowing for accurate measurement of gas emissions over at least 2 minutes. A transparent cling wrap made from polyethylene serves as an enclosure, providing a cost-effective way to capture gases emitted by fruits. The enclosure is replaced after each use to avoid contamination. The sensors detect gas concentrations and send these values along with user input on the type and number of fruits, through the Blynk user interface to the Raspberry Pi. The AI model on the RPi analyzes the ripening stages of the fruits.

2.1.1. Integration of the artificial intelligence model on the Raspberry Pi and fruit grade prediction

This process involves training and exporting the trained model in a compatible format. The model is then transferred to the Raspberry Pi, the necessary libraries are installed, and a Python script written to load the model and process real-time sensor data. The Raspberry Pi is then configured to run this script at startup, enabling continuous monitoring and analysis. The results are displayed on the liquid crystal display (LCD) and the Blynk app.

2.1.2. Testing and performance analysis of the device

A variety of fruits (bananas, oranges, and apples) with different ripeness levels are gathered for testing. Each fruit is placed within the sensor's detection range to measure ethylene and ethanol levels, and the results are saved in a comma-separated values (CSV) file along with the environmental conditions (temperature and humidity) and fruit grades. These fruit's grades are then compared with manual visual and physical assessments of ripeness. Repeated tests are conducted to ensure consistent results, and inconsistencies are addressed by reviewing the AI model and sensor integration and making necessary adjustments to improve accuracy.

2.2. Fruit expiry predictor design specifications (hardware)

The development of a circuit diagram for the FEP resulted from thorough research into the identified problem and the envisioned solution. A series of well-considered trade-offs and decisions led to the selection of the following components:

- Microcontroller (MCU): Raspberry Pi 4 – 4 GB RAM
- DHT22 temperature and humidity sensor
- MQ-3 ethanol sensor
- C_2H_4 winsen electrochemical ethylene sensor

- Logic level converters
- ADS1115 analog-to-digital converter
- LCD display with I2C interface
- Indicators: LED (red), buzzer, and power indicator (green LED)
- Power supply (9 V battery)

2.2.1. DHT22 sensor integration

The digital humidity and temperature sensor (model 22) (DHT22) output is connected to 10k and 20k resistors in series, as the resistor's output falls in the range of its input voltage which is 5 V. The resistors divide the voltage to a value tolerable by the RPI's 3.3 V. In (1) explains how the values of R1 and R2 connected to the DHT22 sensor are gotten.

$$V_{out} = V_{in} \times \frac{R_2}{R_2 + R_1} \quad (1)$$

where: $R_2 = 20$ K,
$R_1 = 10$ K,
$V_{in} = 5$ V,
$V_{out} = 3.3$ V.

The 4.7 K resistor connected to the output of the voltage divider circuit serves as a pull-up resistor. It is used to keep the signal line HIGH even when the sensor is not actively sending any output. This tells the RPI that everything is as it should be, but the sensor is not active at some intervals in time. The value of the resistor is calculated using as (2):

$$R_{pull-up} = \frac{V_{cc}}{I_{input}} \quad (2)$$

Where Vcc is the supply voltage of the DHT22, which is 5 V, and I_{input} from Table 1 is the maximum current, the device can sink when pulling the line low, 1.5 mA. The closest standard and readily available resistor value to the calculated value is 4.7 K ohms. Table 1 is the DHT22 temperature and humidity sensor datasheet snippet showing its parameter characteristics and specifications.

Table 1. DHT22 datasheet snippet

Item	Condition	Min	Typical	Max	Unit
Power supply	DC	3.3	5	6	V
Current supply	Measuring	1		1.5	mA
	Stand-by	40	Null	50	uA
Collecting seriod	Second		2		Second

2.2.2. Winsen electrochemical ethylene sensor integration

The Winsen electrochemical sensor outputs current, and the ADS1115 reads voltage. To convert the current from the sensor to a voltage value within the AD1115 range of tolerable voltage (0 to the voltage of the power source (3.3 V), we use Ohms law, in (3), to calculate the resistor value where V = IR. Where, V is the maximum voltage of the ADC, and I is the maximum output current of the sensor. Allowance for safety is giving at 10% of the maximum voltage of the ADC. Allowance is not a fixed number but merely a safety buffer.

10% of 3.3=0.33 V
V=3.33–0.33=3 V

The maximum output current of the sensor, I is calculated as;

$$\text{Sensitivity} \times \text{Maximum concentration} = 1.8 + 0.3\ \mu\text{A/ppm} \times 100\ \text{ppm} = 0.00021\ \text{A}$$

$$\text{Resistor value} = \frac{3}{0.00021} = 15{,}000\ \Omega$$

Table 2 is the ethylene electrochemical sensor datasheet snippet showing its parameter characteristics and specifications.

Table 2. Ethylene electrochemical sensor datasheet snippet

Detection gas	ETO
Measurement range	0-20 ppm
Max detecting concentration	100 ppm
Sensitivity	(1.8±0.3) µA/ppm
Resolution ratio	0.1 ppm
Response time	<120 s
Bias voltage	300 mV
Load resistance	10 Ω (recommended)
Repeatability	<2% output value
Stability (/month)	<2%
Output linearity	Linear
Zero drift (-20 ºC - 40 ºC)	4 ppm
Storage temperature	15%-90%RH no condensation
Storage humidity	-20 ºC-50 ºC
Pressure range	Standard atmosphere ±10%
Anticipated using life	2 years

2.2.3. Integration of indicators

The calculations for the current limiting resistor of the LED is done using (4):

$$R = \frac{V_{source} - V_{LED}}{I_{LED}} \quad (4)$$

where: $V_{source(red)}$=3.3 V,
$V_{source(green)}$=5 V,
V_{led}=2 V,
I_{led}=0.02 A,
For $R_{red}=\frac{3.3-2}{0.02\,A}$=65 Ω, and
For $R_{green}=\frac{5-2}{0.02\,A}$=150 Ω.

The resistor at the base of the transistors were derived from in (5):

$$R_B = \frac{V_{GPIO} - V_{BE}}{I_B} \quad (5)$$

where V_{GPIO} is the voltage level of the GPIO pin, 3.3 V, V_{BE} is the base-emitter voltage drop of the transistor, and I_b is the base current needed to saturate the transistor.

$$I_B = \frac{I_c}{h_{fe}} \quad (6)$$

The transistor BC547 datasheet specifies a base resistor greater than 660 Ω with the calculation shown in (7). We therefore used a 1 KΩ resistor, meaning the base current will be 2.6 mA, which is within the acceptable range for the BC547 (>660 Ω).

$$\frac{3.3\text{ V} - 0.7\text{ V}}{5\text{ mA}} = 660\ \Omega \quad (7)$$

Table 3 is the BC547 datasheet snippet showing its parameter characteristics and values. The diode connected across the buzzer terminals (commonly known as a flyback or freewheeling diode) is there to protect the circuit from voltage spikes generated when the buzzer is turned off. The 1N4148 diode is chosen for its fast-switching characteristics and low forward voltage drop, making it well-suited for this protective role in buzzer circuits.

Table 3. BC547 datasheet snippet

Collector-emitter saturation voltage	
IC = 10 mA	IB = 0.5 mA
IC = 100 mA	IB = 5.0 mA
IC = 10 mA	

2.3. Hardware implementation

The circuit diagram was implemented using two breadboards, with the layout of the breadboard serving as a guide during the connection process. This connection was done using the design of the breadboard as a guide. The flexibility of the breadboard allowed for rapid experimentation and iteration during circuit design without the need for permanent connections. Figure 2 shows the breadboard connection. The soldered FEP device on the Veroboard is shown in Figure 3, while Figure 4 shows the internal view of the FEP with the plastic enclosure.

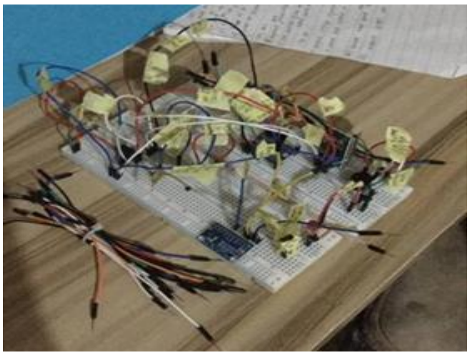


Figure 2. Breadboard connection of the FEP

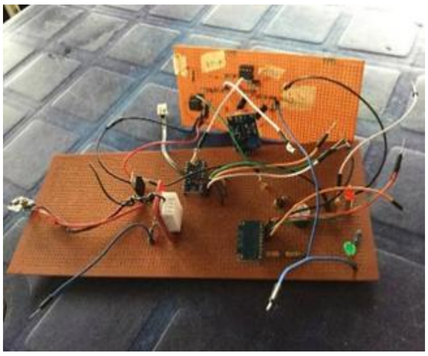


Figure 3. Soldered connection of the FEP

Figure 4. Internal view of the FEP

2.4. Design specifications (software)

The software component of this project is essential for achieving the goal of forecasting the exact hours at which climacteric fruits will spoil, using climatic circumstances, and fruit features as factors. The software design is comprised of two primary components: the development of the AI model and the integration of software and hardware.

2.4.1. Artificial intelligence model development

The main objective of the AI model is to precisely forecast the number of hours till spoilage of climacteric fruits under specific conditions. This entails the examination of environmental variables such as temperature, humidity, ethylene, and ethanol gas concentrations, in addition to the quantity and variety of fruits (e.g., apples and bananas). Model development began with exploratory data analysis (EDA) to understand the distributions of various features and their relationships with the target variable, grade of fruit. This stage helped identify outliers, missing values, and potential feature interactions. Next, feature engineering was performed to transform raw data into a format more suitable for modelling. This included encoding categorical variables like fruit type using one-hot encoding and creating new features that might better capture the predictive signals in the data. Initially, the random forest regressor (RFR) was chosen due to its efficiency in handling outliers, capacity to model non-linear relationships, extensive data-preprocessing, and advantages offered by its ensemble learning methodology. However, after using various machine learning algorithms, the XGBoost model proved to be more effective. The model was evaluated using several metrics, including root mean squared error (RMSE) for a direct measure of prediction error, and R-squared for understanding the proportion of variance in the target variable explained by the model. Python was selected due to its extensive ecosystem of data science and machine learning libraries and its ease of integration with various hardware components. Libraries such as pandas for data manipulation, NumPy for numerical operations, scikit-learn for machine learning algorithms and model evaluation, and matplotlib for data visualization were utilized throughout the model development process.

2.4.2. Software and hardware integration

The system is designed to integrate real-time data acquisition from hardware sensors with a software-based prediction model. Sensor data on temperature, humidity, ethylene, and ethanol levels are collected and processed in real-time to serve as input for the prediction model. The dataset used was obtained from Kaggle. It contained 8670 measurements of ethylene gas level, ethanol gas level, temperature, and humidity readings of relatively equal width/class interval. These parameters are known to significantly influence the ripening process and subsequently, the expiration of climacteric fruits. The dataset’s structure and the relevance of each feature to the project’s goal were confirmed through preliminary data inspection, ensuring a solid foundation for model development.

2.4.3. Data preprocessing

Cleaning: initial steps in data preparation involved cleaning the dataset to ensure its quality and reliability. This included addressing missing values, which were handled appropriately based on the nature of each feature. For continuous variables like temperature and humidity, missing values were imputed using statistical methods (i.e., median or mean imputation), maintaining the integrity of the dataset. Feature Engineering: to enhance the model’s predictive capability, feature engineering was used to transform raw data into a more informative set of inputs. This involved generating derived variables that could have a direct impact on fruit expiration, such as the ratio of ethylene to ethanol, which might indicate the ripening stage more accurately than isolated measurements. Encoding categorical variables ensures that the model can process all types of inputs efficiently. Normalization/standardization: given the varying scales of the features (e.g., gas levels vs temperature readings), the data underwent normalization to bring all variables to a common scale. This step is crucial for models that are sensitive to the scale of input features, ensuring that no single feature disproportionately influences the model's predictions due to its scale. Hyperparameters: the booster used is gbtree, the objective is squared error, while verbosity is 100. With a learning rate of 0.01 and a maximum depth of 4. The n_estimator is 1500 while the early stopping round is 50. The data was divided into 80/20 for training and testing.

2.5. Simulation of model

After the development of the system, extensive testing was carried out to confirm its accuracy, reliability, and applicability in real-world scenarios. This phase was dedicated to evaluating the performance of several predictive models, including the support vector regression (SVR), decision tree regressor, RFR, and the XGBoost model, with a focus on the XGBoost model. They were subjected to testing against different datasets to validate their performance comprehensively.

2.5.1. Model evaluation

Among the models tested, the XGBoost model delivered superior performance. It was evaluated using a reserved portion of the dataset, comprising 30% of the total data, selected to represent a wide array of conditions ensuring a thorough and indicative assessment.

2.5.2. Software implementation

Main script: this is responsible for coordinating the sensor data collection and making real-time predictions using the trained machine learning model. It runs on the Raspberry Pi and ensures continuous monitoring and grading of fruits based on ethanol and ethylene levels. Below is an overview of the main script:
- Initialize the sensors and load the predictive model.
- Collect data from the sensors at regular intervals.
- Process the collected data and make predictions using the trained model.
- Output the predicted grade of the fruit.

2.5.3. Method of testing and performance analysis

After the design and development of the fruit expiry predictor, it become necessary to test its performance. The following steps were carried out.

– Preparation of sample fruits: selection of a sample set of fruits: banana, orange, apple, to be tested individually, type wise and one at a time, quantity wise, ensuring a variety of ripeness levels for comprehensive testing.
– Run the device: each fruit, at its time of testing, is placed within the detection range of the gas sensors and run the device to obtain the ethylene and ethanol levels.
– Record data: save the output results, including the temperature and humidity of the environment and the fruit grade, in a CSV file for each fruit tested.
– Validate results: manually inspect the tested fruits and compare the device's grade with visual and physical assessments of ripeness.
– Statistical analysis: analyze the recorded data for consistency and accuracy using statistical methods. Check for patterns or discrepancies in the device's grading compared to manual assessments.
– Repeat tests: conduct repeated tests on the same fruits to ensure the device provides consistent results over time.
– Review and adjust: if inconsistencies are found, review the AI model and sensor integration, and make necessary adjustments to improve accuracy.

3. RESULTS AND DISCUSSION

In this section, the proposed system's outcome is presented as a solution to the problems highlighted in the introduction, including challenges to classify fruit ripeness using the CIELAB color, and that of using an electronic nose. This system is therefore designed and developed around advanced sensing and AI models for real-time monitoring of ethylene levels and temperature in forecasting the spoilage of fruits in real-time. Figure 5 is the Blynk interface showing the user's ability to input the number of fruits, type of fruit, start the device, and get the grade of the fruit, designed for a better user experience.

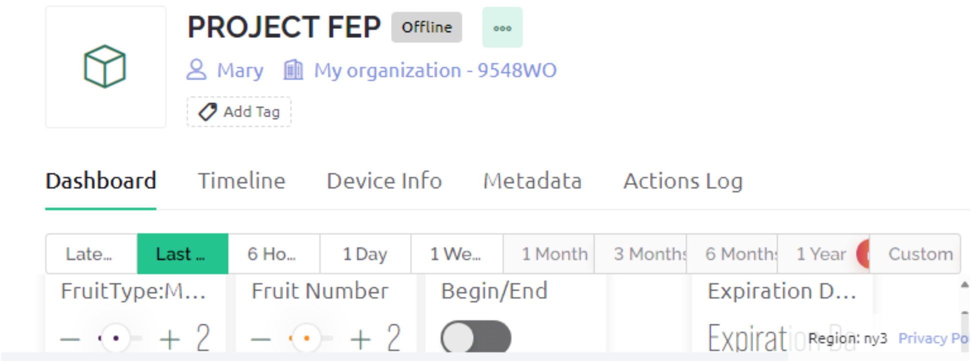


Figure 5. Blynk user interface

3.1. Model testing

A detailed evaluation was conducted to determine the most accurate model for estimating the grade of the climacteric fruits. This process involved comparing multiple machine learning algorithms, including the decision tree regressor, SVR, and the XGBoost model.

Decision tree regressor performance analysis: the decision tree regressor, a model characterized by its simplicity and interpretability, yielded an R^2 score of 0.9559366284038163. This score indicates that the model accounts for approximately 95.6% of the variance within the target variable, showcasing a commendable level of predictive accuracy. However, when juxtaposed with the ensemble-based approach of the random forest algorithm, the decision tree exhibited a marginal deficit in performance, likely attributable to its propensity for overfitting in comparison to ensemble methods [28].

SVR performance analysis: the application of SVR to this predictive task resulted in an R^2 score of 0.8760372604135744, indicating a moderately high level of predictive accuracy. However, this score is lower relative to the other models evaluated. This outcome suggests that the SVR model, while proficient at capturing non-linear relationships within datasets, may not be the best fit for this specific predictive task. The performance might be hindered by the SVR model's sensitivity to hyperparameter settings and feature scaling [29]. This underscores the importance of meticulous tuning and optimization to achieve the best possible results with SVR.

RFR performance analysis: distinguished by its ensemble methodology, the RFR demonstrated superior predictive capability, as evidenced by an R^2 score of 0.9986202019833746. This metric elucidates the model's efficacy in explaining approximately 99.86% of the variance associated with the expiration hours of climacteric fruits. The algorithm's robustness against overfitting, coupled with its capacity to model complex, non-linear relationships through the aggregation of numerous decision trees [30], renders it the most suitable choice for deployment.

XGBoost model performance analysis: this emerged as the most proficient model, with an R^2 score of 0.9925533245669792, signifying its unparalleled effectiveness in explaining the variance associated with the expiration hours of climacteric fruits.

After the testing of the various models, they were compared on two performance metrics, which are the R-squared and the RMSE. Table 4 shows the performance comparison between the various models, with XGBoost outperforming other models.

Table 4. A performance comparative table between models

Models	R- squared	RMSE
DTR	0.9559	37.9141
SVR	0.8760	0.4578
RFR	0.9986	0.1122
XGBoost	0.9925	0.0483

3.1.1. Justification for model selection

The comprehensive analysis decisively identifies the XGBoost model as the optimal choice for this predictive application, given its highest R^2 score and advanced algorithmic attributes tailored to meet the challenge at hand. The empirical evidence from the evaluation phase solidifies the decision to deploy the XGBoost model for predicting the expiration hours of climacteric fruits, marking a significant advancement in predictive accuracy and model efficiency.

3.2. Fruit expiry predictor testing

This section aims to illustrate the practical application of the FEP. It contains images of the device in action, predicting the grade of fruit spoilage as shown in Figure 6.

Figure 6. Device predicting the grade of a spoilt banana

Here, bananas were place inside the fruit expiry predictor to determine their status. A total of 33 bananas were used. While some were predicted as been ripe, other were predicted as been overripe or unripe. In Figure 6, we see the predictor showing that the banana is rotten, that is spoilt.

3.3. Result validation

After the FEP testing, the results obtained were used to separate the good bananas from the spoilt or unripe ones. The results from the FEP’s prediction of the quality of bananas are summarized in Table 5. 16 out 33 results are shown in the Table 5.

Table 5. FEP's prediction of the quality of 33 bananas (showing 16 out of the 33)

ID	Temp	Humidity	Ethanol	Ethylene	Overall state
1	26.9	86.9	236	227	Spoilt
2	26.9	86.9	216	205	Spoilt
3	26.9	86.9	289	136	Overripe
4	26.9	86.9	319	138	Overripe
5	26.9	86.9	303	158	Overripe
6	26.9	86.9	247	161	Overripe
7	26.9	86.9	274	175	Overripe
8	26.9	86.9	260	153	Overripe
9	26.9	86.9	148	145	Ripe
10	26.9	86.9	186	134	Ripe
11	26.9	86.9	111	101	Unripe
12	26.9	86.9	104	135	Unripe
13	26.9	86.9	114	107	Unripe
14	26.9	86.9	166	160	Ripe
15	26.9	86.9	116	160	Unripe
16	26.9	86.9	136	170	Ripe

4. CONCLUSION

The objective of the research was to design a predictor to foretell the expiration of fruits using ethylene gas to meet the widespread problem of fruit wastage. This work thus developed an ethylene-based sustainable system that can predict fruit freshness without any mistakes. It merges temperature and ethylene gas sensors with an AI model for instant solutions of fruit quality. This work successfully plans and executes the hardware, builds the AI model, and integrates the system with the Blynk application in a user-friendly manner. Though this work is designed to predict fruit expiry date, its test was limited to bananas only in a real-life scenario and proved successful. The results indicate that the method can potentially reduce fruit wastage and stimulate sustainable food consumption choices. Future research includes increasing the dataset to include a wider array of fruits, and possibly, environmental conditions will improve the AI model's accuracy and robustness. Also, exploring opportunities for scaling up production and commercializing the device can facilitate broader adoption and impact.

ACKNOWLEDGMENTS

This work was supported by the Research Cluster of Covenant University Centre for Research, Innovation and Discovery (CUCRID), Covenant Applied Informatics and Communication Africa Centre of Excellence (CApIC-ACE), and Federated Genomic (FEDGEN).

FUNDING INFORMATION

The authors state no funding is involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Olabode Idowu-Bismark	✓				✓				✓	✓		✓		✓
Anyiam Chinemere Eberchukwu	✓					✓				✓		✓		
Oluwadamilola Oshin		✓			✓					✓				
Ibiang Emmanuel	✓	✓	✓				✓	✓	✓		✓			
Tonwe Mary	✓	✓	✓				✓	✓	✓		✓			
Emmanuel Adetiba				✓		✓				✓	✓		✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] C. Chen, A. Chaudhary, and A. Mathys, "Nutritional and environmental losses embedded in global food waste," *Resources, Conservation and Recycling*, vol. 160, 2020, doi: 10.1016/j.resconrec.2020.104912.

[2] M. A. Augustin, L. Sanguansri, E. M. Fox, L. Cobiac, and M. B. Cole, "Recovery of wasted fruit and vegetables for improving sustainable diets," *Trends in Food Science and Technology*, vol. 95, pp. 75–85, 2020, doi: 10.1016/j.tifs.2019.11.010.

[3] E. L. Barrera and T. Hertel, "Global food waste across the income spectrum: Implications for food prices, production and resource use," *Food Policy*, vol. 98, 2021, doi: 10.1016/j.foodpol.2020.101874.

[4] N. P. Nirmal *et al.*, "Valorization of Fruit Waste for Bioactive Compounds and Their Applications in the Food Industry," *Foods*, vol. 12, no. 3, 2023, doi: 10.3390/foods12030556.

[5] J. Gao, Y. Zhang, Z. Li, and M. Liu, "Role of ethylene response factors (ERFs) in fruit ripening," *Food Quality and Safety*, vol. 4, no. 1, pp. 15–20, 2020, doi: 10.1093/fqsafe/fyz042.

[6] R. H. Cristescu, K. Goethals, P, B. Banks, F, N. Carrick, and C. Frère, "Experimental Evaluation of Koala Scat Persistence and Detectability with Implications for Pellet-Based Fauna Census," *International Journal of Zoology*, 2012, doi: 10.1155/2012/631856.

[7] S. Janssen, K. Schmitt, M. Blanke, M. L. Bauersfeld, J. Wöllenstein, and W. Lang, "Ethylene detection in fruit supply chains," *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, vol. 372, no. 2017, 2014, doi: 10.1098/rsta.2013.0311.

[8] J.-C. Pech, A. Latché, and M. Bouzayen, "Ethylene Biosynthesis," in *Plant Hormones*, Dordrecht: Springer Netherlands, 2010, pp. 115–136, doi: 10.1007/978-1-4020-2686-7_6.

[9] Y. Liu *et al.*, "The Molecular Regulation of Ethylene in Fruit Ripening," *Small Methods*, vol. 4, no. 8, 2020, doi: 10.1002/smtd.201900485.

[10] U. C. Ukpong *et al.*, "Deep reinforcement learning agents for dynamic spectrum access in television whitespace cognitive radio networks," *Scientific African*, vol. 27, 2025, doi: 10.1016/j.sciaf.2024.e02523.

[11] F. Mendoza and J. M. Aguilera, "Application of image analysis for classification of ripening bananas," *Journal of Food Science*, vol. 69, no. 9, 2004, doi: 10.1111/j.1365-2621.2004.tb09932.x.

[12] O. Oshin, J. Amenaghawon, F. Moninuola, and O. Idowu-Bismark, "Class Attendance System Using Facial Recognition," *Ingenierie des Systemes d'Information*, vol. 30, no. 6, pp. 1589–1595, 2025, doi: 10.18280/isi.300617.

[13] M. Baietto and A. D. Wilson, "Electronic-nose applications for fruit identification, ripeness and quality grading," *Sensors (Switzerland)*, vol. 15, no. 1, pp. 899–931, 2015, doi: 10.3390/s150100899.

[14] E. Llobet, E. L. Hines, J. W. Gardner, and S. Franco, "Non-destructive banana ripeness determination using a neural network-based electronic nose," *Measurement Science and Technology*, vol. 10, no. 6, pp. 538–548, 1999, doi: 10.1088/0957-0233/10/6/320.

[15] M. Li, D. C. Slaughter, and J. F. Thompson, "Optical chlorophyll sensing system for banana ripening," *Postharvest Biology and Technology*, vol. 12, no. 3, pp. 273–283, 1997, doi: 10.1016/S0925-5214(97)00059-8.

[16] A. S. M. F. A. Haque, M. A. Hakim, and R. Hafiz, "CNN Based Automatic Computer Vision System for Strain Detection and Quality Identification of Banana," in *2021 International Conference on Automation, Control and Mechatronics for Industry 4.0 (ACMI)*, Jul. 2021, pp. 1–6, doi: 10.1109/ACMI53878.2021.9528269.

[17] N. Aherwadi, U. Mittal, J. Singla, N. Z. Jhanjhi, A. Yassine, and M. S. Hossain, "Prediction of Fruit Maturity, Quality, and Its Life Using Deep Learning Algorithms," *Electronics (Switzerland)*, vol. 11, no. 24, p. 4100, Dec. 2022, doi: 10.3390/electronics11244100.

[18] M. Vijayalakshmi and V. J. Peter, "CNN based approach for identifying banana species from fruits," *International Journal of Information Technology (Singapore)*, vol. 13, no. 1, pp. 27–32, 2021, doi: 10.1007/s41870-020-00554-1.

[19] S. Chakraborty, F. M. J. M. Shamrat, M. M. Billah, M. Al Jubair, M. Alauddin, and R. Ranjan, "Implementation of Deep Learning Methods to Identify Rotten Fruits," in *Proceedings of the 5th International Conference on Trends in Electronics and Informatics, ICOEI 2021*, Jun. 2021, pp. 1207–1212, doi: 10.1109/ICOEI51242.2021.9453004.

[20] Y. Li, X. Feng, Y. Liu, and X. Han, "Apple quality identification and classification by image processing based on convolutional neural networks," *Scientific Reports*, vol. 11, no. 1, 2021, doi: 10.1038/s41598-021-96103-2.

[21] H. M. R. Iqbal and A. Hakim, "Classification and Grading of Harvested Mangoes Using Convolutional Neural Network," *International Journal of Fruit Science*, vol. 22, no. 1, pp. 95–109, Dec. 2022, doi: 10.1080/15538362.2021.2023069.

[22] S. H. M. Ashtiani, S. Javanmardi, M. Jahanbanifard, A. Martynenko, and F. J. Verbeek, "Detection of mulberry ripeness stages using deep learning models," *IEEE Access*, vol. 9, pp. 100380–100394, 2021, doi: 10.1109/ACCESS.2021.3096550.

[23] R. E. Saragih and A. W. R. Emanuel, "Banana Ripeness Classification Based on Deep Learning using Convolutional Neural Network," in *3rd 2021 East Indonesia Conference on Computer and Information Technology, EIConCIT 2021*, 2021, pp. 85–89, doi: 10.1109/EIConCIT50028.2021.9431928.

[24] S. Naik, Y. Rana, and V. Thakkar, "Mango (Mangifera Indica L.) Classification Using Shape, Texture and Convolutional Neural Network Features," 2022, pp. 237–245, doi: 10.1007/978-981-16-5987-4_25.

[25] A. Septiarini, H. Hamdani, H. R. Hatta, and A. A. Kasim, "Image-based processing for ripeness classification of oil palm fruit," in *Proceeding - 2019 5th International Conference on Science in Information Technology: Embracing Industry 4.0: Towards Innovation in Cyber Physical System, ICSITech 2019*, 2019, pp. 23–26, doi: 10.1109/ICSITech46713.2019.8987575.

[26] "What is SDG 13? - ESG | The Report," [Online]. Available: https://esgthereport.com/what-is-sdg-13-the-united-nations-sustainable-development-goal-for-climate-action/. (Accessed: Mar. 19, 2024).

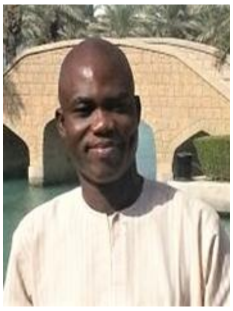
[27] F. Ohunakin *et al.*, "Climate change education (CCE) in informal workplaces: Unearthing possibilities and limitations for SDG 13 actualization," in *International Conference on Science, Engineering and Business for Driving Sustainable Development Goals, SEB4SDG 2024*, 2024, doi: 10.1109/SEB4SDG60871.2024.10630448.

[28] A. R. Panda, S. Roy, M. K. Mishra, S. Sahoo, S. Mohapatra, and M. K. Gaurisaria, "Hyperparameter Tuning of Machine Learning Models: Analysing Student's Depression Data," in *ESIC 2025 - 5th International Conference on Emerging Systems and Intelligent Computing, Proceedings*, 2025, pp. 907–912, doi: 10.1109/ESIC64052.2025.10962651.

[29] K. Pandey and S. Patel, "A Theoretical Perspective and Experimental Evaluation of the Extensive Analysis of Loss Functions in Machine Learning and Deep Learning," in *2024 Asia Pacific Conference on Innovation in Technology, APCIT 2024*, 2024, doi: 10.1109/APCIT62007.2024.10673427.

[30] K. Yunus, H. Miraç Pektaş, and H. Çelik. "Artificial intelligence applications in education: Natural language processing in detecting misconceptions," *Education and Information Technologies*, vol. 30, no. 3, pp. 3035-3066, 2025, doi: 10.1007/s10639-024-12919-1.

BIOGRAPHIES OF AUTHORS



Olabode Idowu-Bismark is a senior lecturer at the Department of Electrical and Information Engineering, Covenant University, Ota, Nigeria. He holds a B.Eng. degree in Electrical and Electronics Engineering from the University of Benin, Nigeria, and a M.Sc. in Telecommunications Engineering from Birmingham University, UK. He obtained his Ph.D. in Information and Communication Engineering from Covenant University. He has worked in various companies as an engineer, senior engineer, and technical manager. He is a Faculty Member of the Covenant Applied Informatics and Communication Africa center of excellence (CApIC-ACE), and FEDGEN Cloud Computing Research Project (World Bank and AFD funded). He is a member of the Nigerian Society of Engineers, a member of MIEEE, and a COREN Registered Engineer. His research interests are in the areas of machine learning for mobile communication, mmWave communication, MIMO systems, and OTFS for MIMO communication. He has published many scientific papers in international peer-reviewed journals and conferences. He can be contacted at email: olabode.idowu-bismark@covenantuniversity.edu.ng and idowubismarkolabode@gmail.com.

Anyiam Chinemere Eberchukwu is a faculty member and a Ph.D. student of Covenant University. Also, a member of the Nigerian Society of Engineers (NSE). Her research interests and experiences include machine intelligence, renewable energy, and electrical power. She has competence in MATLAB simulation, renewable energy technologies power converters ATP-EMTP Data Analysis SQL Python, SPSS, Microsoft Office, Excel, TeX/LaTeX. She can be contacted at email: chinemere.owuama@covenantuniversity.edu.ng.

Oluwadamilola Oshin received the Ph.D. degree in information and communication engineering (with a focus on nano-electronic biosensing) from Covenant University, Nigeria, in 2020. She is a Senior Lecturer of information and communication engineering with the Department of Electrical and Information Engineering, Covenant University. She is also a Faculty Member of the Covenant Applied Informatics and Communication Africa Centre of Excellence (CApIC-ACE), a World Bank ACE-IMPACT Centre, Covenant University. She has broad research experiences and interests, including mobile communications, data analytics, artificial intelligence (AI), and MEMS-based biosensing. She is professionally registered with the Council for the Regulation of Engineering in Nigeria (COREN) and is also a senior member of the Institute of Electrical and Electronics Engineers (IEEE). She enjoys teaching, research and solving health-related issues using engineering and technology. She can be contacted at email: damilola.adu@covenantuniversity.edu.ng.

Ibiang Emmanuel is a full-stack Engineer and a first-class graduate from Covenant University, where he studied Electrical and Electronics Engineering. He graduated in 2024. He tech journey is rooted in his love for solving problems, whether that is crafting sleek and responsive user interfaces with TypeScript and Next.js or digging into backend operations with Node.js, MySQL, and MongoDB. He also utilizes Tailwind CSS for its seamless integration of design and functionality. He can be contacted at email: emmanuel.ibiang@stu.cu.edu.ng.

Tonwe Mary is a graduate of Electrical and Electronic Engineering from Covenant University. She graduated with first-class honors in 2024. She works at the intersection of AI, electronics, and data, designing systems that not only perform well under ideal conditions but also adapt in environments where energy is scarce, infrastructure is fragile, and scalable intelligence must be intentional. Her area of research interest includes artificial intelligence (AI), data analysis, embedded systems, context-aware computing, and low power systems. She can be contacted at email: mary.tonwe@stu.cu.edu.ng.

Prof. Emmanuel Adebita (Member, IEEE) received the Ph.D. degree in information and communication engineering from Covenant University, Ota, Nigeria. He was the Director of the Center for Systems and Information Ser vices (aka ICT Center), Covenant University, from 2017 to 2019. He is the incumbent Deputy Director of the Covenant Applied Informatics and Communication Africa Centre of Excellence (CApIC-ACE) and a Co-PI of the FEDGEN Cloud Computing Research Project at the center (World Bank and AFD funded). He is the Founder and a Principal Investigator of the Advanced Signal Processing and Machine Intelligence Research (ASPMIR) Group. He is a Full Professor and the former Head of the Department of Electrical and Information Engineering, Covenant University, from 2021 to 2023. He is also an Honorary Research Associate (HRA) with the Institute of System Sciences and a Visiting Research Associate with the KZN e-Skills Co-Laboratory, Durban University of Technology, Durban, South Africa. He was a recipient of several past and ongoing scholarly grants from reputable bodies, such as World Bank; France Development Agency (AFD); Google; U.S. National Science Foundation; Durban University of Technology, South Africa; Nigeria Communications Commission; Rockefeller Foundation; International Medical Informatics Association (IMIA); and hosts of others. He has authored/coauthored more than 100 scholarly publications in journals and conference proceedings, some of which are indexed in Scopus/ISI/CPCI. His research interests and experiences include machine intelligence, software defined radio, cognitive radio, biomedical signal processing, and cloud and high-performance computing (C&HPC). He is a registered engineer (R.Engr.) with the Council for the Regulation of Engineering in Nigeria (COREN) and a member of the Institute of Information Technology Professional (IITP), South Africa. He can be contacted at email: emmanuel.adetiba@covenantuniversity.edu.ng