FruitfulInsight: IOT and ML Based System to Predict Expiry of Fruits

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***Abstract*— This study discusses a project introducing an integrated food quality checking system, merging Internet of Things (IoT) and machine learning technologies. The system encompasses intelligent hardware and advanced algorithms. The primary objective is to combat the common issue of non-preservative food spoilage due to various factors. Leveraging machine learning and IoT, the project aims to provide effective solutions to this problem in the form of a low-cost, portable electronic nose (Smart electronic nose) that can predict the expiry of fruits so that they can be consumed accordingly. The sensors, featuring metal oxide semiconductor - the MQ2 sensor and DHT11 sensor are interfaced with Arduino Uno and Node MCU for creating, storing, and analyzing the dataset containing the levels of gas emission, humidity, and temperature of fruits with the help of machine learning algorithms and IOT. After utilizing various regression algorithms such as Linear Regression, Random Forest Regression, K-Nearest Neighbors (KNN), and Support Vector Regression (SVR), the Smart electronic nose was finally able to predict the expiry of bananas with a Mean Squared Error (MSE) of 0.1207. This underscores its potential in assessing fruit freshness and predicting expiry dates, contributing significantly to reducing food wastage.**

Keywords— IoT, Machine Learning, Electronic Nose, KNN, Support Vector Regressor, Decision Tree Regressor, Food Expiry

I. INTRODUCTION

In India there is no label of expiration on fruits and vegetables and hence it is not easy to determine the expiration time or use by time in terms of fruits. This causes a large amount of wastage by both the consumers and the wholesaler. The expiration time is estimated in a regulated setting, the food is tested by the manufacturer, and it just implies a best before time. But it experiences maltreatment and temperature swings on the way from the farm to the refrigerator. Consequently, food is wasted in vast amounts every day all over the world due to the inaccuracy of the expiration time prediction by just the looks of the vegetables and fruits. Farmers frequently store their food goods in warehouses for extended periods of time before distributing them, which results in significant food waste because a single defective batch generally degrades quickly. This leads to significant losses by the farmers, which raises prices and has an obstructive effect on the economy. One of the main causes of the variations in fruit and vegetable prices is this.

The use of computer technology to identify the various phases of banana ripening has been studied previously [1]. One proposed feature is the ability to assess the ripeness of a fruit by examining its skin color. The dual electronic nose (Smart electronic nose)/camera setup demonstrates Fisher class separability [14]. There are 4 stages of maturity in banana —unripe, partially ripe, fully ripe, and overripe—are perfectly categorized in this instance [2]. In a different technique, data from a sample and sensor chamber was gathered and shown using a Raspberry Pi 3 Version B. Seven different MQ sensor types made up the sensor chamber, which was used to detect gas emitted through Filipino food that is tomato-based [3].

While these methods might work, they would demand a significant amount of memory and processing power to store the data and execute machine learning algorithms. Instead, we've addressed the drawback by employing humidity sensor , gas sensor and temperature sensor that can detect the release of volatile gasses from various food items, such as tomatoes and bananas. We created the dataset ourselves using the readings we acquired from these sensors. Using the ESP8266 module, the gas sensor [MQ2] was connected via the IoT application Blynk [13]. Data was collected by the sensors while the banana was within the sample chamber. A CSV file was created containing the values that were automatically logged in. We collected the data for seven days and saw an incremental graph of the gasses captured by the MQ2 sensor. Utilizing the acquired data, we implemented machine learning techniques. This technology can be used by food producers, food processors, and supermarkets to store food in warehouses, check food quality in real-time, and provide consumers with complete openness about the food they eat. Food can be consumed, donated, or turned into compost if people are aware of when it will go bad. In this manner, food waste can be drastically decreased, and conventional methods of food disposal—which raise CO2 levels—can be avoided. The ability of a farmer to forecast and arrange the transportation of his produce is one of the agro benefits. A farmer can be alerted immediately as one sample of the goods is ripe and ready, allowing him to sell it right away. To conserve the other items, the algorithm can also alert him if a particular batch of fruits ripen beyond its prime.

Along with the advantages, the project offers several more that may be investigated. Various fruits are stored in warehouses, such as banana, the first banana to start ripening releases a gas called ethylene, which sets off a chain reaction of ripening among the other fruits [4]. This gas also triggers the ripening process in other bananas, causing them to mature more quickly than anticipated. Minimizing food waste demands a watchful eye on the environment in which it's kept. IoT and Machine Learning can empower us to be vigilant guardians of our food stores, reducing spoilage and maximizing utilization.

II. Literature survey

Spoilage is still a major cause of massive economic losses and chronic midwinter (food poison) tragedies for consumers all over the planet. In the global food supply chain, food spoilage is still one of the unaddressed significant problems that causes economic losses and health risks to the consumers [11]. What's the problem? Food-spoilage testing usually relies on human inspections, which is time consuming and error prone. In recent years, the integration of the Internet of Things (IoT) and machine learning (ML) has emerged as a promising approach to address this challenge. In this review we will examine the development and application of smart electronic noses (e-noses) for food quality testing. This section also talks about the sensors used by Smart's electronic noses and tongues, comparing them in terms of limitations, applications and principles.

Algorithms such as PCA, SVM and machine learning classifiers may be used to identify the attributes of food samples [15]. It has occasionally been used in conjunction with other classifiers to assess the quality of food. ID3 served as the decision tree's training algorithm. The decision tree is constructed using a greedy, top-down method. As a result, some characteristics of food quality may also be evaluated using decision trees and RF. The preparation of samples and sampling depends on temperature and humidity as gas sensors are often quite sensitive to these variables. To get a high degree of accuracy, even the number of observations needs to be substantial. Additionally, Smart electronic nose use a lot of energy, which limits their capacity. Since both PCA and ANN were designed for static features, only time-invariant data could be identified [5]. Therefore, it was necessary to build a smart electronic nose that was smaller, less susceptible to external environmental factors, required less energy, and still provided an elevated degree of accuracy. Furthermore, it was necessary to improve the Smart electronic nose's usability.

A study suggested a low-cost, metal oxide semiconductor-based (Smart electronic nose) sensor that could distinguish between a banana's various ripening phases. With a support vector machine (SVM), it was able to distinguish between the scent fingerprints of bananas with an accuracy of 98.66%. A system for sampling, a gas sensor array, a system for data collection, and pattern identification algorithms comprised the first 4 stages of the experimental setup. Fifteen bananas of different colors, sizes, and weights were put inside the sample chamber, which was temperature-controlled and monitored, along with the amount of gas level (ethylene). Six MOS sensors (MQ-3, MQ Server-5, the MQ-9, MQ-131, MQ135, and MQ-136) made up the cycloid gas chamber. A data acquisition card was used to record the gas sensor's readings in the computer, from which important data could be extracted. The techniques for data analysis included the analysis of principal components (PCA), linear discriminant evaluation (The LDA), SIMCA, and SVM. SVM may be applied to non-linear data and divides categories using a hyper-plane that optimizes a measure known as margins. Consequently, an economical MOS-based Smart electronic nose was created to recognize and distinguish between a Smart electronic nose's several ripening phases. Nevertheless, further research is required to create more sensors, and the ideal number of sensors has to be estimated [5].

Another experiment was conducted where Pork freshness was determined using an Smart electronic nose (the PEN2, Air sense Data Analytics, GmBH, France) that comprises of a sensor arrangement an auto-sampling device, and pattern recognition software. Various MOS sensors, including the W6S, W1C, & W3C models, make up the sensor array. During the sampling process, variables such as the mass of the pork examples, storage duration, and headspace-generation duration were taken into account to identify the ideal experimental setup. [7] Pork samples were categorized using Back Propagation Neural Networks (BPNN) and LDA (Linear Discriminant Analysis) [16] with an accuracy of 97.14% based on storage times (ST). The sensory ratings were predicted using multiple linear regression. The Smart electronic nose signal's strong correlation coefficient ($R2 = 0.9848$) with the sensory ratings indicates that it is a reliable tool for determining the freshness of pork. The outcome demonstrated that viscosity and odor sensory ratings decreased with longer storage times, particularly beyond the third day. As a result, the algorithms used were able to categorize the samples of pork throughout the time of storage, forecasting duration of storage and the sensory evaluations. They were properly categorized by BPNN, well-discriminated by LDA, and MLR supplied the quality index. The PEN2 Smart electronic nose isn't widely accessible and is quite pricey. To improve accuracy and range, more machine-learning algorithms must be created [9].

Another study discusses the development of electronic noses for automated volatile chemical detection [10] They have addressed the potential uses of a digital nose in the fields of food, medicine, and the environment, as well as describing and developing a rudimentary prototype of one. Neural Networks (ANN) with a sensor array make up Electronic Nose. Every chemical vapor, when picked up by a sensor, leaves behind a unique signature or pattern. A database containing those signatures will be produced by introducing various chemical vapors. After that, ANN is employed to examine the intricate database and locate the chemical vapor. A prototype was constructed that included sensors for temperature and humidity in addition to nine tin-oxide vapor sensors. This prototype's artificial neural network (ANN) was a multilayer feed-back network that had been constructed using the fuzzy ARTmap and backpropagation algorithms. Five different chemicals were used to test this prototype: vinegar, acetone, ammonia, isopropanol, and lighter fluid. After employing randomly chosen training patterns, the two networks were trained to an accuracy of between 89.7% and 98.2%. In the medical profession, this electronic nose can analyze bodily scents to identify potential issues.

In another experiment, a smart electronic nose equipped with ten MOS sensors was used to forecast the freshness of postharvest kiwifruit [8]. To differentiate between the fruit at various stages, three distinct feature extraction techniques were employed: max/min numbers, differences values, and 70th values. Furthermore, the variables hardness, soluble solids percentage (SSC), and overall ripeness were predicted using SVM, RF, and a partial least-squares regression approach (PLSR). The three characteristics were utilized in conjunction with LDA to categorize the various ripening phases. When it came to overall ripe (training: $R2 = 0.9928$; testing: $R2 = 0.9928$), SSC (training: $R2 = 0.9749$; testing: $R2 = 0.9143$), and firm (training: $R2 = 0.9814$; testing: $R2 = 0.9290$), the RF algorithm performed the best.

Another study intends to evaluate the efficacy of a quick gas chromatography (GC) electrosensor. The detection of volatile eggs, the measurement of interior quality, and the sensory evaluation were the three studies carried out. The sensory characteristics tested were the color of the yolk and albumen, spreading ratio, freshness, and overall acceptability. Findings indicated that a reduction in albumen height caused Haugh unit values to drop as storage duration increased. To further analyze the data, discriminant factor analysis, and principal component analysis were employed. These supported the variation in the volatile profiles of the egg samples and explained 95.7% and 93.71% of the overall variation, respectively. As a result, it was determined that the rapid GC Smart electronic nose is a trustworthy tool for estimating and evaluating the freshness of eggs [6].

III. Block Diagram

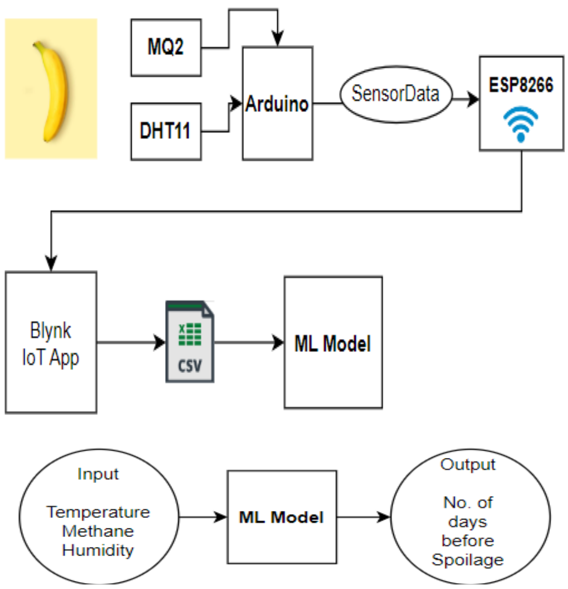

Fig. 1. Example of a figure caption.

IV. Implementation

This idea has not been widely explored so, we could not find any pre-existing dataset that aligned with our specific needs. Consequently, we opted to create a custom dataset by employing a banana and several sensors. The subsequent sections outline the various stages of our implementation.

A. Proof of Concept

The MQ2 excels at sniffing out diverse gasses, including those emitted by ripening fruit. Its core is a ceramic sensor element adorned with metal oxide semiconductors. When powered, the element heats up, amplifying its sensitivity to target gasses.To maintain an ideal operating temperature, the MQ2 employs an integrated heating element, ensuring consistent performance. Fig. 2. is the image that we took during the proof of concept stage of our project. The figure shows sensors, hardware and the connections required for the purpose stated earlier.

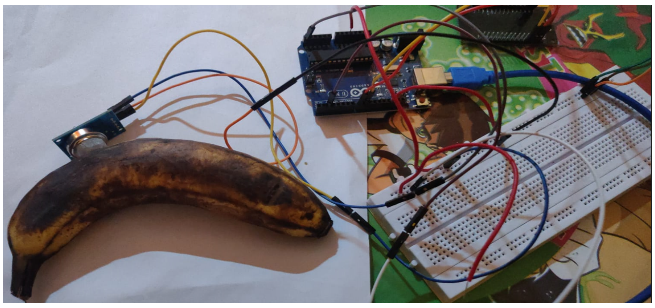

Fig. 2. Proof of Concept.

To ensure that the MQ2 sensor was the right choice for this project, we incorporated an ESP8266 to establish a real-time connection between the gas sensor MQ2, temperature and humidity sensor DHT11, and the Blynk IoT application. Our testing involved examination of a banana's ripening process, during which we measured the gases it emitted, along with monitoring temperature and humidity. As the banana ripened, we observed a gradual increase in gas concentrations, showcasing the practical application of the MQ2 sensor in developing a cost-effective Smart electronic nose.

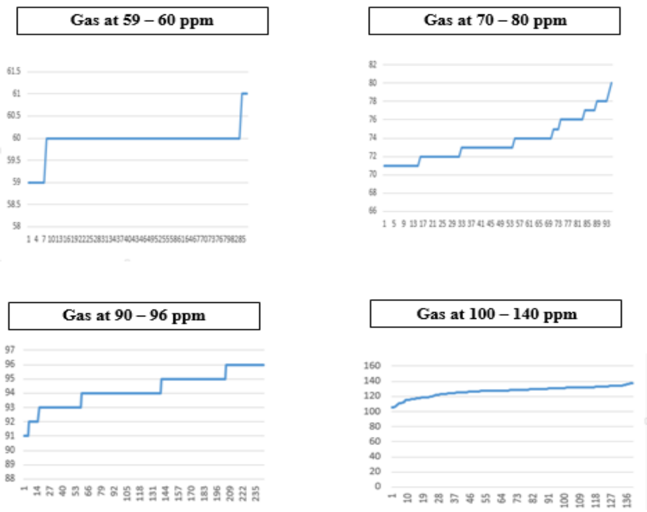

Fig. 3. Graphs showing an increase in gas concentration over a week.

B. Hardware Selection

Our sensor selection concentrated on practicality and versatility of the sensors within the budget. In this case, the MQ2 gas sensor was highly preferred in this category because it could detect a range of gasses at low-cost prices making it ideal for our multi-gas monitoring needs. The

DHT11 temperature and humidity sensor also fell nicely into place with one unit that could measure any kind of environment accurately and at a reduced cost. Communication and integration were easier when using NodeMCU due to its built-in Wi-Fi capabilities which meant that the IoT integration was possible for sending data wirelessly. Finally, as part of this strong combo, Arduino Uno made sense due to its presence in the market, being user-friendly, and its compatibility with selected sensors which made it an appropriate platform for data processing along with sensor interfacing.

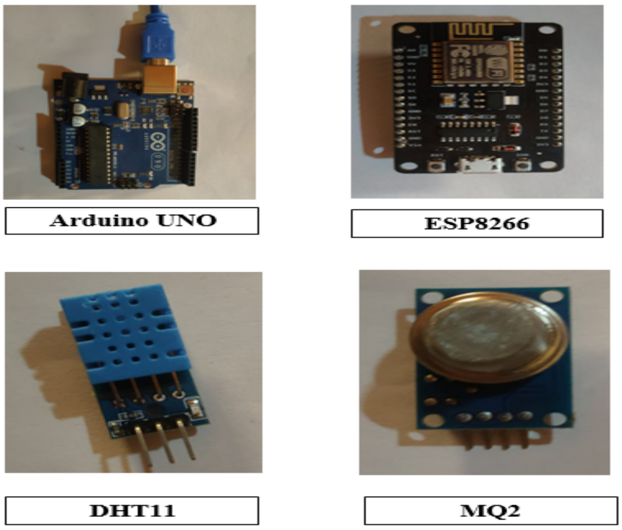

Fig. 4. Hardware Used.

C. Connections

We connected the DHT11 temperature and humidity sensor to an Arduino digital pin and used a DHT library to sense and manipulate environmental data. For the MQ-2 gas sensor, we connected it to an Arduino analog pin and modified our code to measure the values of gas concentration. To achieve seamless communication, we made use of UART serial communication between the Arduino and NodeMCU through RX and TX pins respectively. We wrote a program on Arduino that coordinates data from both sensors while on NodeMCU we developed a code for receiving serial data. By means of its built-in Wi-Fi features, NodeMCU wirelessly sent the collected data to the Blynk server thus allowing us to monitor and capture sensor data very easily.

D. Isolated Sampling Pod

To ensure the cleanliness of the setup, it was regularly cleaned with a lint-free cloth thereby enabling us to create an airtight and isolated environment quite meticulously. Gasses that had accumulated within the sampling pod were systematically released before each subsequent measurement to ensure that the readings remained intact. Moreover, we introduced a DHT11 sensor in our dataset which provides additional attributes such as temperature, and humidity for our machine learning model.

E. Data Collection

In our experiment, we introduced an unripe banana into the sampling pod. The gas sensor MQ2, situated within the small chamber, was powered by a DC supply [5V] via an Arduino module. Simultaneously, the Arduino board was connected to temperature and humidity sensors. Initially, the gas sensor heated up for a few minutes upon measurement commencement. Sensor data was recorded & logged into a CSV file, using commas as delimiters, and displayed on the serial interface of the Blynk IOT App. Repeating this process at different times of the day produced substantial data stored in various CSV files. Combining matching columns from each CSV file generated a sizable dataset suitable for training our machine-learning model.

TABLE I. FIRST 10 DATA POINTS OF THE DATASET

Different Features in the Dataset				
Index	*Gas(ppm)*	*Temperature(C)*	*Humidity*	*Remaining Days*
1	51	21	42	7
2	52	21	42	7
3	52	21	42	7
4	52	20	42	7
5	53	21	42	7
6	53	21	42	7
7	53	21	42	7
8	53	20	42	7
9	54	21	43	7
10	54	21	43	7

F. Stationarity

Over a period of time, there is an observable upward trend in the concentration of gas, indicating that it possesses characteristics of non-stationarity. On the other hand, temperature and humidity exhibit cyclical patterns and stationary behavior as they consistently fluctuate within a specific range. Moreover, during the ripening process of fruits, there is an exponential increase in gas concentration once it surpasses a predetermined threshold. This surge can be attributed primarily to the release of ethylene gas.

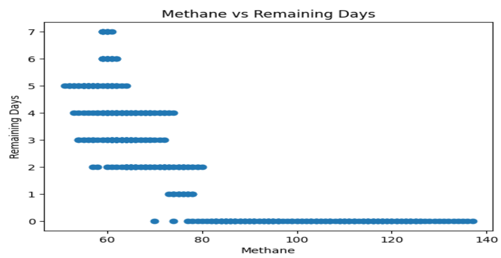

Fig. 5. Scatter Plot of Gas Concentration.

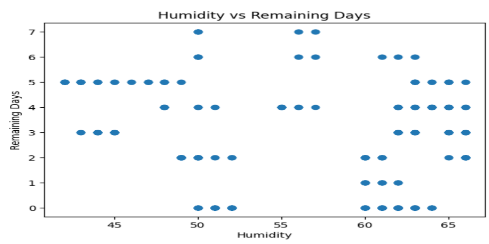

Fig. 6. Scatter Plot of Humidity.

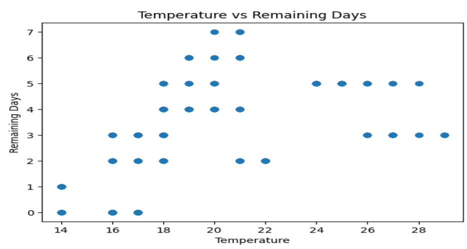

Fig. 7. Scatter Plot of Temperature.

G. Data Cleaning

The initial assessment was conducted with a careful examination of the data plot to identify outliers in the line which showed sensitivity by the gas sensor to humidity and temperature changes.Moreover, based on the initial flat graph of the fruit's constant gas concentration, we decided selectively not to consider starting points till some meaningful insights were visible. This methodical approach attempted to refine the dataset so that only pertinent variations in gas concentration could be analyzed in detail.

H. Model Training

In our project, we used Python for data management, preparing the data, and training the models. The dataset had four main sections: temperature, humidity, and PPM gas concentration as input variables while the last column represented the target value which is the shelf life that our model aimed to predict. The Matplotlib Library helped us analyze the data more clearly, allowing us to navigate through data efficiently and understand the dataset more clearly.

In order to avoid potential biases in the data and make it more simply available, we base normalization of any numeric feature (temperature; humidity or gas concentration) on Sklearn StandardScaler. We trained many different models: K-Nearest Neighbors (KNN) regressor and Decision Tree, Support Vector Regression (SVC), Logistic Regression, that is how precision was increased in our machine learning approach.

V. Result

A. Result Table

For quick reference, the following table of regression metrics is taken from our own analysis. It gives a convenient idea of how well our machine learning model is doing. Our machine learning model consists of Mean Squared Error (MSE), Root Means SquareError (RMSE) and R-squared. The MSE and RMSE are the average squared differences between predicted values and actual values. R-squared is the measure of goodness of fit for the model.

TABLE II. Regression Metrics for various Models

Regression Metrics			
Machine Learning Models	***Mean Squared Error (MSE)***	***Mean Absolute Error (MAE)***	***R-Squared (R2)***
Support Vector Regressor	0.1719	0.3017	0.9617
K Neighbors Regressor	0.4136	0.3035	0.9101
Linear Regression	0.3092	0.4555	0.9288
Decision Tree Regressor	0.2029	0.1352	0.9568

B. Learning Curve

Data from research must be divided into two parts: training and testing. In this way, we ensure that our model has enough information to solve the problem while keeping the data clean so as not to bias our work. As a result, we looked at the learning curves carefully, which illustrate how the performance of the model changes with different sizes of training datasets. Therefore, a 75/25 split was selected after an extensive analysis. This allowed for adequate data on which to build the model yet retain enough portion (25%) for unbiased tests thereby upholding our results' generalizability and validity.

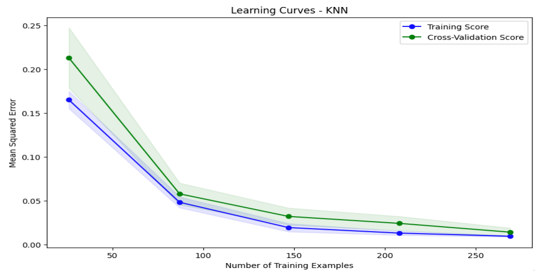

Fig. 8. Learning Curve of KNN Regressor

C. Predicted vs Actual Plot

Following scatter plots shows the relationship between actual and predicted values.

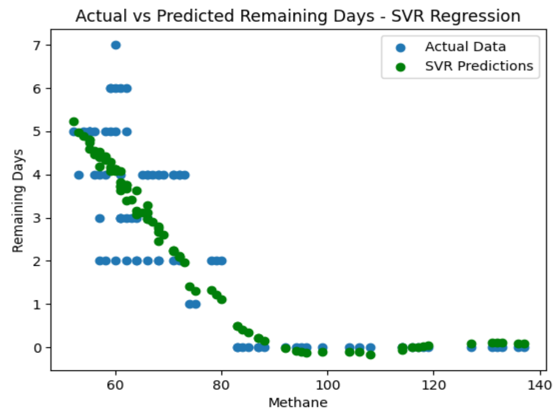

Fig. 9. Plot for Support Vector Regression

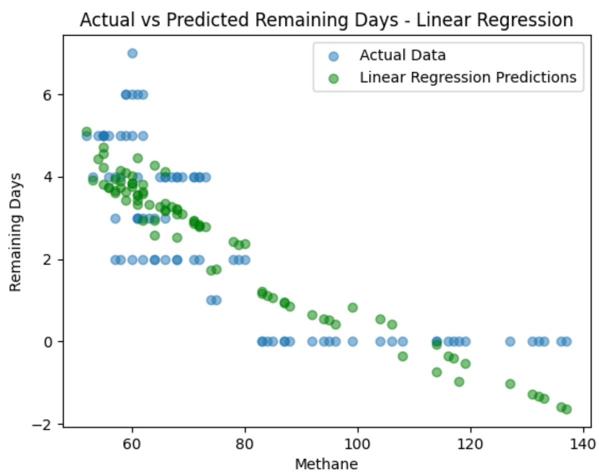

Fig. 10. Plot for Linear Regression

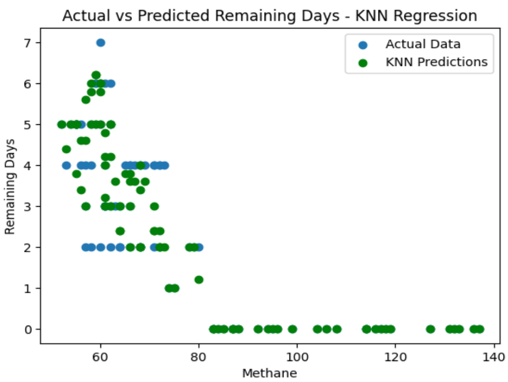

Fig. 11. Plot for KNN Regression

VI. Conclusion

Combating food waste is imperative in our era of heightened sustainability awareness. This project leverages cutting-edge technologies, namely machine learning and the Internet of Things (IoT), to propose a novel solution for optimizing food storage and minimizing unnecessary waste. This sensor-based project, applied initially to the case study of banana ripening, accurately maps the evolving gas profile, particularly the emission of methane and ethylene, across various stages of the fruit's maturity. Employing a battery of machine learning algorithms, including K-Nearest Neighbors, Decision Trees, and Support Vector Machines, we were able to achieve a remarkable 0.12 MSE in predicting the expiration date of the banana specimens. This initial success demonstrates the immense potential of this affordable smart nose, in conjunction with powerful machine learning techniques, to significantly reduce food waste by enabling precise expiration date prediction in a domestic setting. Further research is warranted to validate and refine this approach across a wider range of food items and explore its potential integration into smart technologies.

VII. Future Scope

Apart from bananas, our model can be applied to other fruits such as apples and avocados that have recorded ethylene and ethane emissions which hold a promising potential for ripeness assessment [12]. A Raspberry Pi integrated with advanced image recognition algorithms is suggested to improve our analysis. Consequently, the camera would be able to detect not only color changes like the browning of apple peels but also evaluate texture patterns that indicate spoilage in kiwi skins. Food processors may predict expiry dates more accurately, leading to minimal waste in their inventory management.

References

[1] Magno, R. D. C., Bersamen, P. J. S., & Valiente, L. D. (2022, December). Monitoring of Banana Ripening Process and Identification of Banana type using FRCNN, LSTM, And Color Segmentation. In 2022 IEEE 14th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM) (pp. 1-6). IEEE.

[2] Saputro, A. H., Juansyah, S. D., & Handayani, W. (2018, May). Banana (Musa sp.) maturity prediction system based on chlorophyll content using visible-NIR imaging. In 2018 International Conference on Signals and Systems (ICSigSys) (pp. 64-68). IEEE.

[3] Pangilinan, J. R., Legaspi, J., & Linsangan, N. (2022, December). InceptionV3, ResNet50, and VGG19 Performance Comparison on Tomato Ripeness Classification. In 2022 5th International Seminar on Research of Information Technology and Intelligent Systems (ISRITI) (pp. 619-624). IEEE.

[4] Anoop, A., Thomas, M., & Sachin, K. (2021, August). IoT Based Smart Warehousing using Machine Learning. In 2021 Asian Conference on Innovation in Technology (ASIANCON) (pp. 1-6). IEEE..

[5] Ansari, A. Q., Khusro, A., & Ansari, M. R. (2015, December). Performance evaluation of classifier techniques to discriminate odors with an E-Nose. In 2015 Annual IEEE India Conference (INDICON) (pp. 1-5). IEEE..

[6] Al-Bukhaiti, W. Q., Noman, A., Qasim, A. S., & Al-Farga, A. (2017). Gas chromatography: Principles, advantages and applications in food analysis. International Journal of Agriculture Innovations and Research, 6(1), 2319-1473.

[7] Chen, J., Gu, J., Zhang, R., Mao, Y., & Tian, S. (2019). Freshness evaluation of three kinds of meats based on the electronic nose. Sensors, 19(3), 605.

[8] Du, D., Wang, J., Wang, B., Zhu, L., & Hong, X. (2019). Ripeness prediction of postharvest kiwifruit using a MOS e-nose combined with chemometrics. Sensors, 19(2), 419.

[9] Ye, Z., Liu, Y., & Li, Q. (2021). Recent progress in smart electronic nose technologies enabled with machine learning methods. Sensors, 21(22), 7620.

[10] Khorramifar, A., Karami, H., Lvova, L., Kolouri, A., Łazuka, E., Piłat-Rożek, M., ... & Darvishi, Y. (2023). Environmental Engineering Applications of Electronic Nose Systems Based on MOX Gas Sensors. Sensors, 23(12), 5716.

[11] Hammond, S. T., Brown, J. H., Burger, J. R., Flanagan, T. P., Fristoe, T. S., Mercado-Silva, N., ... & Okie, J. G. (2015). Food spoilage, storage, and transport: Implications for a sustainable future. BioScience, 65(8), 758-768.

[12] Ji, Y., & Wang, A. (2021). Recent advances in phytohormone regulation of apple-fruit ripening. Plants, 10(10), 2061.

[13] Rana, S., Gopal, L., & Gupta, N. (2021, December). Smart city concepts, features and the role of internet of things: a review. In 2021 International Conference on Computational Performance Evaluation (ComPE) (pp. 585-591). IEEE.

[14] Chen, S., Wang, X. X., Hong, X., & Harris, C. J. (2006). Kernel classifier construction using orthogonal forward selection and boosting with Fisher ratio class separability measure. IEEE transactions on neural networks, 17(6), 1652-1656.

[15] Ahmed, T., Paul, R. R., Alam, M. A., Hasan, M. T., & Rab, M. R. (2022, March). Performance Comparison of Different Machine Learning Classifiers in Categorizing Bangla News Articles. In 2022 4th International Conference on Natural Language Processing (ICNLP) (pp. 376-379). IEEE.

[16] Al-Sammarraie, N. A., Al-Mayali, Y. M. H., & El-Ebiary, Y. A. B. (2018, July). Classification and diagnosis using back propagation Artificial Neural Networks (ANN). In 2018 International conference on smart computing and electronic enterprise (ICSCEE) (pp. 1-5). IEEE.

[17] Merzlyak, M. N., Gitelson, A. A., Chivkunova, O. B., & Rakitin, V. Y. (1999). Non‐destructive optical detection of pigment changes during leaf senescence and fruit ripening. Physiologia plantarum, 106(1), 135-141.

[18] Merzlyak, M. N., Gitelson, A. A., Chivkunova, O. B., & Rakitin, V. Y. (1999). Non‐destructive optical detection of pigment changes during leaf senescence and fruit ripening. Physiologia plantarum, 106(1), 135-141.

[19] Kathirvelan, J., & Vijayaraghavan, R. (2017). An infrared based sensor system for the detection of ethylene for the discrimination of fruit ripening. Infrared Physics & Technology, 85, 403-409.

[20] Sun, M., Yang, X., Zhang, Y., Wang, S., Wong, M. W., Ni, R., & Huang, D. (2018). Rapid and visual detection and quantitation of ethylene released from ripening fruits: the new use of Grubbs catalyst. Journal of agricultural and food chemistry, 67(1), 507-513.

[21] Brady, C. J. (1987). Fruit ripening. Annual review of plant physiology, 38(1), 155-178.

[22] Okeke, E. S., Okagu, I. U., Okoye, C. O., & Ezeorba, T. P. C. (2022). The use of calcium carbide in food and fruit ripening: Potential mechanisms of toxicity to humans and future prospects. Toxicology, 468, 153112.

[23] Janssen, S., Schmitt, K., Blanke, M., Bauersfeld, M. L., Wöllenstein, J., & Lang, W. (2014). Ethylene detection in fruit supply chains. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 372(2017), 20130311.

[24] Mim, F. S., Galib, S. M., Hasan, M. F., & Jerin, S. A. (2018). Automatic detection of mango ripening stages–An application of information technology to botany. Scientia horticulturae, 237, 156-163.

[25] Vijayakumar, D. T., & Vinothkanna, M. R. (2020). Mellowness detection of dragon fruit using deep learning strategy. Journal of Innovative Image Processing, 2(1), 35-43.