DETECTION OF PESTICIDE CONTAMINATION AND FRESHNESS IN FOODS USING NON-DESTRUCTIVE METHODS OF IOT & ML

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ABSTRACT

The growing population of our current and next generation is facing high risk from pesticide contamination, spoilage, and adulteration in food. Based on the UN 2017 report, ~2 lakh people die each year from pesticide poisoning. About 30% to 40% of food get spoilt every year which leads to high economic and health impact. In the last few decades, the world population has increased drastically but cultivable land has decreased over time. To fulfil the increased food demand and desire to increase profit, at times food is adulterated or sprayed with pesticides above prescribed limit, causing long-term harm to environmental and human beings.

This paper proposes a solution named "eJagruk" which can act as a clearinghouse for safe, fresh, and healthy food using intelligent and scientific techniques. It is a comprehensive food testing solution that combines a multi-layer analysis model (with IOT sensors, image processing), multi-parameter (with light spectrum, gas, moisture, image pixel) using novel statistical analysis based methods. The data input is captured near to real-time by 1) light receiver sensor, 2) gas sensor 3) moisture sensor and 4) thermal camera to determine pesticide residue and freshness in food items making use of a novel non-destructive technique

KEYWORDS

Food pesticide detection using IOT, Pesticide detection using Image processing, Food freshness detection

1. INTRODUCTION

Pesticides are commonly used in modern agriculture to control weeds, pests [1] and to augment food production [2]. Optimal use of pesticides can prevent losses in agriculture from pest infections and diseases [3]. However, the excessive use or abuse of pesticides in agriculture can lead to high pesticide residues (above the prescribed limit) in food and the environment, which can have an adverse impact on human health through the food chains [4]. Today most of the countries in the world are facing challenges in the detection and management of pesticide contamination (e.g., Organophosphorus and organonitrogen) and freshness in foods and are looking for an innovative non-destructive low-cost solution that can be deployed easily at any time at any place. India ranks second in the production of vegetables in the world and accounting ~13.4% of the world's production (based on available country wise government data). India, like other countries, is also facing challenges in the detection and management of freshness and pesticide contamination in foods. Based on surveys by reputed institutes, ~50%-70% [5] of fruit and vegetable production are contaminated with pesticide residues higher than the prescribed limit. To maximize profit and meet the increasing demands, pesticide and adulterant is used in farm used above the prescribed limit to get more quantity of food in a short period. At the other end, consumers do not have any low-cost non-destructive solution to test pesticide contamination on the foods that they are consuming.

Today there is an increasing trend of growing fruits, vegetables either artificially or infected with several pests' chemicals. The most common category of similar chemicals are Organophosphorus pesticide such as Chlorpyrifos, Malathion and artificial ripeners such as calcium carbide/ethephon and oxytocin respectively which causes long-term harm in the food chain [6].The traditional methods for detecting pesticide residues are usually based on laboratory instrumental techniques and methods such as liquid chromatography–mass spectrometry (LC-MS) [7] , gas chromatography (GC) [8], high performance liquid chromatography (HPLC) [9], or chromatographic methods coupled with mass spectrometry (MS) detectors [10]. These traditional methods for detecting freshness and pesticide in food items are the laboratory methods which are time-consuming and costly. These methods involve complicated sample pre-treatments and require highly trained technicians and expensive equipment for the food testing.

The objective of the research is to enable citizens and organizations to detect the presence of pesticide contamination (above prescribed maximum residue limit) and freshness in food items using low-cost, non-destructive methods quickly with a good accuracy. This paper proposes a solution named "eJagruk" which will act as a clearinghouse for safe, fresh, and healthy food using intelligent and scientific techniques. The research proposes a comprehensive food testing solution that combines a multi-layer analysis model (with IOT sensors, image processing) on multi-parameter (with light spectrum, gas, moisture, image pixel) using novel statistical analysis methods. The data input is captured near to real-time data by 1) light receiver sensors, 2) gas sensors, 3) moisture sensor and 4) thermal camera and then processed by the statistical analysis methods of IOT and image processing layer as shown in Figure 1 (highlighted the methods with number 2 to 14 in Figure 1). The result from IOT and image processing layer is combined by a statistical algorithm (method 15 in Figure 1) with higher attention weight to IOT layer to determine a decision (method 16 in Figure 1) as 'PASS' or 'FAIL' on pesticide residue and freshness in food items making use of the novel non-destructive technique.

Figure 1 below displays the high-level Functional Diagram of our research solution- "eJagruk".

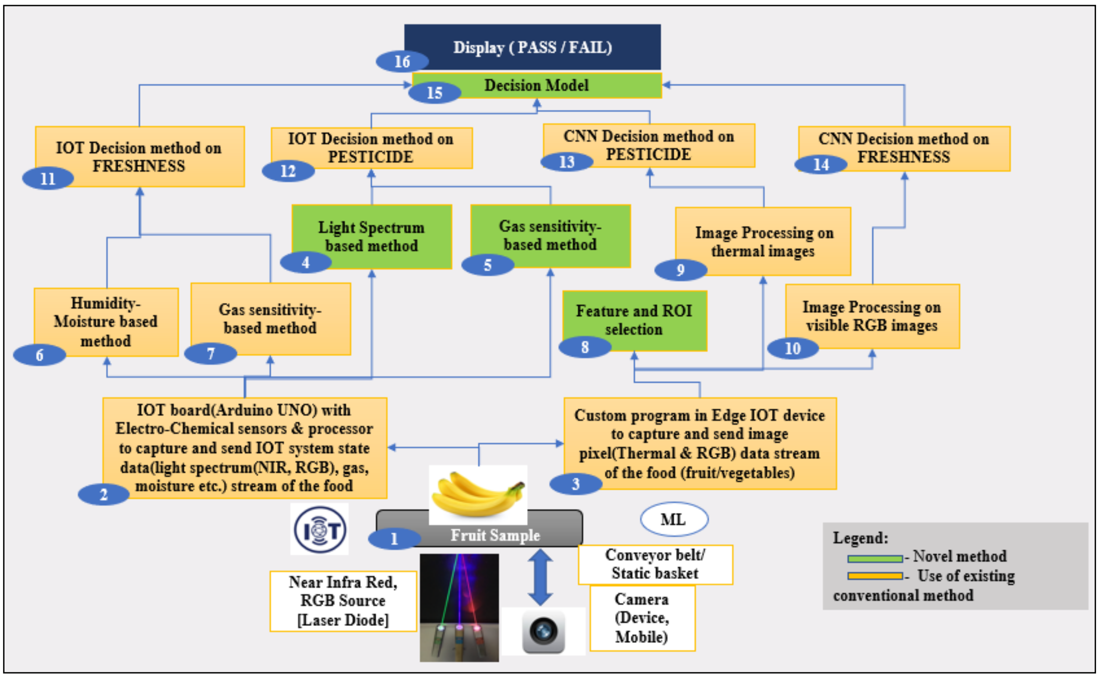

Figure 1: High-level functional diagram

The experiment in our research uses a IOT device, Sensors, Thermal and Red, Green & Blue (RGB) light digital camera and three computing systems.

The first computing system or IOT device collects and analyses sensors data with an analysis model in the IOT layer. The second computing system or virtual machine in the cloud collects and analyse image pixel data with an analysis model in the image processing layer. The third computing system which is another virtual machine in the cloud includes an intelligent decision-making model to decide and display food testing result. This computing system comprises at least one input unit, one decision making unit, and at least one storage unit. The storage unit is a means for saving the food pesticide or freshness record and the output result data.

The first computing input system of IOT layer, is configured to collect the sensed data as a time series sensors data (Light, GAS, Humidity) and apply intelligent automated statistical algorithm such as 1) customized Normalized difference vegetation index (NDVI) method, 2) Relative percentage variation of gas sensor output model, 3) Custom image pixel features reduction model and other methods explained in subsequent sections, to determine probability of pesticide & freshness of food.

The second computing input system of the image processing layer is configured to collect the thermal image pixel of the food and apply intelligent automated statistical algorithm to determine probability of pesticide & freshness of food. The third computing system of the intelligent decision-making layer is configured to collect the output (Probability) of both IOT and image processing model and apply an automated novel statistical algorithm with higher bias weightage to IOT model output to compute final decision as 'PASS' or 'FAIL' on food pesticide residue and freshness testing. The third computing system also includes an user interface to display the result to users in an user-friendly manner.

The research paper in the further section will explain the proposed work and methodology (methods 1 to 16 of Figure 1) in detail along with the result, discussion and conclusion of the research.

2. RELATED WORK

The traditional methods for detecting pesticide residues are usually based on mentioned instrumental techniques and methods such as liquid chromatography–mass spectrometry (LC-MS) [7] , gas chromatography (GC) [8], high performance liquid chromatography (HPLC) [9], or chromatographic methods coupled with mass spectrometry (MS) detectors [10] which are time taking destructive methods to perform and achieve satisfactory testing results of food. The mentioned methods need expensive equipment and highly skilled technicians and are not convenient to popularize and promote.

Scientists are also experimenting with other rapid methods such as flow injection analysis[11], immunoassays [12], spectroscopic analyses [13], and electrochemical techniques [14] provide enzyme linked immunosensor assay and various electro analytical techniques for pesticide testing but none of the solution is economical and user friendly so that common citizen can embrace. These traditional methods require a considerable amount of time for testing sample preparation and provide a given result after a certain lag of time. This limitation results in the need for better detection of freshness and pesticide in food items.

Horiguchi et al. [15] made use of attenuated total internal reflection (ATR) method and Fourier transform (FT) based on Lambert-beer law to detect pesticide particles floating in water. The mentioned ATR method using a prism is used by many scientists for surface analysis of detecting pesticide residue and is applicable to various state samples, such as solid, liquid and powder. The disadvantage of the method is it requires a large & costly spectroscopy apparatus and a method to calculate FT and ATR to determine pesticide residue. Bhandari et al. [16] recommended a method for analysis of a satellite captured image based on Normalized Difference Vegetative Index (NDVI). The method is used to read signatures of different objects using multi-spectral remote sensing process. The study objective was to find vegetative index of different covers and classify them according to NDVI. The NDVI is now an established and commonly used method for determining crop health in agricultural and food processing applications. The NDVI is calculated as

$$NDVI = (\text{Near Infrared} - RED) / \text{Near Infrared} + RED)$$

Scientific analysis on different thresholds of NDVI are applied for finding the false colour composite of objects which are then made to show different landforms.

Riczu et al. [17] survey is popular research in the scientific community which is based on spectral surveys done over the apple orchard using three spectral instruments and then using the investigation results to create normalized differential vegetation index map. The NDVI map then helped to determine the vigour condition of fruit trees in a non-destructive way. Singh, Tejkanwar & Singh, Mandeep. [18] study also reveals that NDVI can be used for pesticide detection, but the study does not consider making use of either image of foods or making use of data based machine learning technology and thereby increasing the accuracy of experiment and removing any bias/error in testing. Madianos, Leonidas & Skotadis [19] presented a paper on the detection of pesticide using a gas sensor based on nanoparticle networks and four distinctive polymer coatings. The nanoparticle network, however, can be costly to use and can face challenges of thermal noise, Brownian motion, stability problem etc.

The study of related art of work reveals that there is a need for innovation to detect the presence of pesticide contamination (above prescribed maximum residue limit) and freshness in food items using low-cost, non-destructive methods quickly with a good accuracy which any citizen or organization can carry, deploy and use easily and quickly.

3. PROPOSED WORK AND METHODOLOGY

While there are various techniques available to detect pesticide and food freshness, this paper proposes a comprehensive food testing solution which combines multi-layer analysis model (with IOT sensors, image processing), multi-parameter (with light spectrum(Near Infra Red (NIR), RGB), gas, moisture, image pixel) using novel statistical analysis using near to real time data captured by 1) light receiver sensor, 2) gas sensor 3) moisture sensor and 4) thermal camera to determine pesticide residue and freshness in food items making use of novel non-destructive technique.

3.1. Method 1: Sample Preparation & Set Up

Step 1: Sample Preperation

In this research, pesticide residue of materials such as

i) Chlorpyrifos (IUPAC name: O,O-Diethyl O-3,5,6-trichloropyridin-2-yl phosphorothioate &

ii) Malathion (IUPAC name: Diethyl 2-[(dimethoxyphosphorothioyl)sulfanyl]butanedioate has been selected for analysis as sulphur-containing organophosphates are commonly used on farms for growing foods (fruits, vegetables).

The analysis has been performed on few fresh and rotten (or not fresh) fruit samples (banana and apple) purchased from the market and grown in local organic farms to test on freshness and pesticide residue. In a few of the fruit samples, pesticide quantity (above the prescribed limit) of Chlorpyrifos, Malathion is injected to get a noticeable result. The sample fruits which are grown in a local organic farm are also being used to set a reference value.

Step 2: Hardware Component Set Up

Figure 2 displays the high-level technical diagram with hardware specification details about various sensors, tools and technology used in our experiment of 'eJagruk' solution. It consists of various hardware modules such as Microcontroller- ATmega328P, NIR laser diode, RGB Diode emitter, light detector Photodiode, light dependent sensor, digital image capture module, gas sensor, moisture sensor, Liquid Crystal Display (LCD) display, AWS cloud storage and VM (Virtual machine) to host the solution etc.

A circuit has been developed using Arduino uno IOT board. NIR Diode laser is used to produce laser induced Near Infra-Red (NIR) of Wavelength=940 nm (Power = 15 mW). RGB Diode Emitter is used to produce RGB light spectrum of Wavelength=400 nm- 600 nm (Power = 15 mW). For the experiment, a static container is used to place the fruit (here, banana) in between a light (NIR, RGB) source and Arduino uno IOT board containing light receiver, light dependent, gas and moisture sensors so that spectrum of light passing through fruit and other system parameters of the fruit sample can be easily detected by sensor array in IOT board.

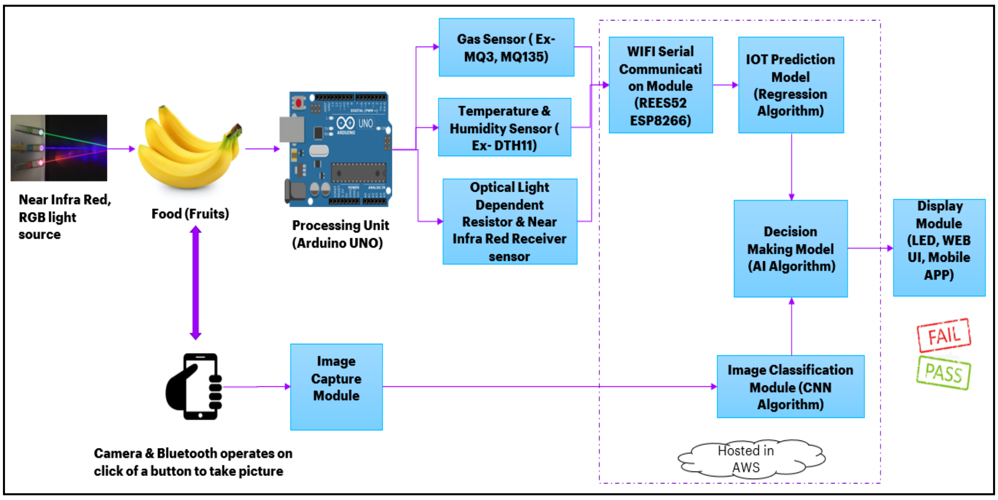

Figure 2. High-level Technical Diagram with Hardware & Software modules

Step 3: Software Component Set Up

As shown in Figure 2, various software technology components and embedded solution used in 'eJagruk' solution experiment.

For our research, the software solution in the edge IOT device cloud is based on

i. Programmable Interface Computers (PIC) simulator with MPLAB (vendor: Microchip Technology) environment support
ii. Arduino Software with Integrated development environment

The embedded system links both hardware and software and enable seamless data capture and processing from IOT devices and sensors. For PIC simulator, a commonly available micro SD card module is used to load the PIC program as shown in Figure 3. Microchip's XC8 and MPLAB IDE is used to create and test the custom program

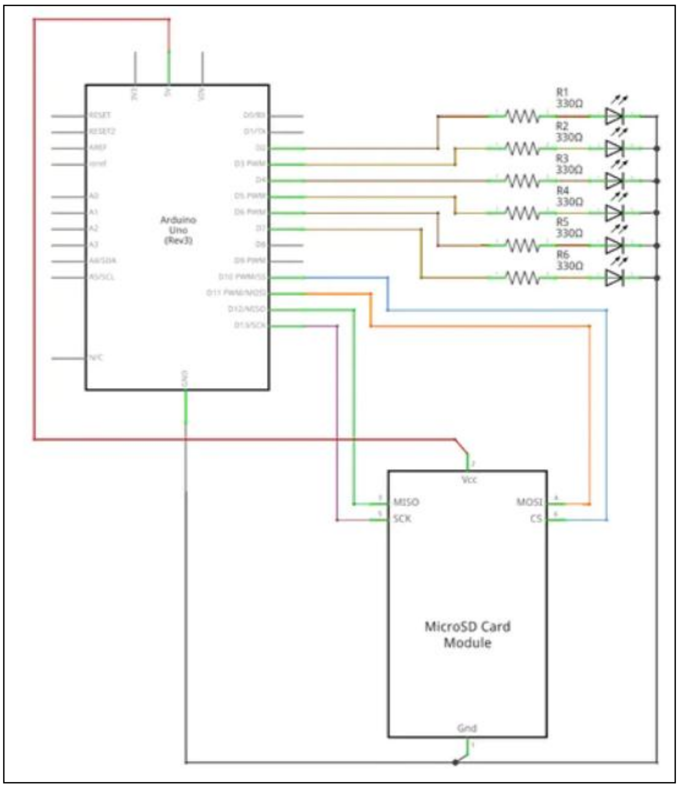

Figure 3: Circuit diagram of Arduino Uno integration with SD card module

The software solution in the cloud is based on open source technology stack hosted in the AWS cloud. The custom program is created to enable low-cost Electro Optical Gas sensors (Light receiver, light dependent, gas, moisture sensors) to send IOT stream data as publish - subscribe messaging to AWS. REST API based custom program is being created for the rest of the communication between IOT edge devices and AWS server.

3.2. Method 2,3: Data Capture

In our experiment, the spectrum of light after passing through the fruit sample is captured by Near-Infra-red receiver photodiode and Light-dependent Sensor with a change in voltage and resistance values.

The photodiode used in our experiment is a semiconductor device(p-n-p) which converts light energy into voltage or current by generating and electron hole pair. The current & voltage produced is directly proportional to the intensity of absorbed light. Similarly, change in resistance of a light-dependent resistor is directly proportional to the intensity of absorbed light. The change in voltage and resistance is mapped automatically with the spectrum of light (NIR, RGB) by eradicating any bias. The information then is streamed into the next processing layer of the program for statistical analysis based on the data captured.

Arduino uno board integrated gas sensors, moisture sensors to capture gas and moisture state information of the fruit sample are placed in a closed contact. The sensor data is calibrated with consideration of moisture, gas state parameters in the static container in which the fruit is placed. The image of the fruit sample is captured using a digital camera module. For our experiment, a phone camera module with attachable Seek Compact Thermal Imager device is used as an option for image (Thermal and RGB) capture.

Figure 4 shows different samples of banana fruit image (RGB) captured and uploaded into AWS cloud virtual machine for further image processing.

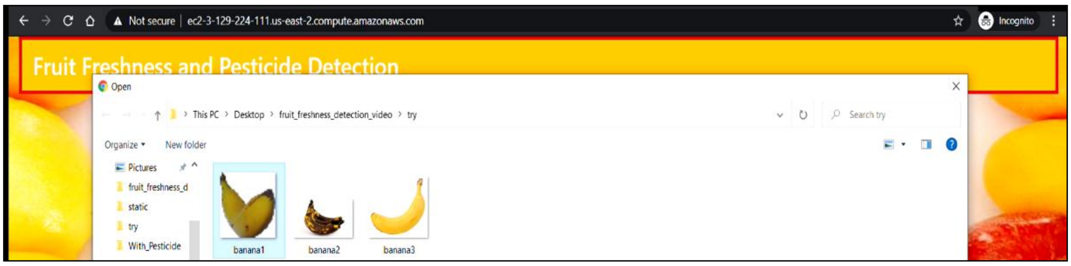

Figure 4. Fruits(banana) images uploaded into AWS VM for testing

Multiple processing methods in Internet of Things (IOT) layer which is explained in subsequent section, processes the sensor data captured using various sensors (Near-Infra-red light receiver and Light-dependent Sensor, Gas sensors, Humidity- Moisture sensors) using statistical algorithm and predicts the confidence percentage of the food (fruit here) having pesticide contamination or food spoilage.

Multiple processing methods in the Machine Learning (ML) layer, which is explained in subsequent section, process the image data captured by a digital camera and perform classification to determine the confidence percentage of the food (fruit here) having pesticide contamination or food spoilage.

3.3. Method 4: Light Spectrum Method for Pesticide Testing

The Light spectrum based method in “eJagruk solution uses RGB light spectrum and Infrared light spectrum to determine Customised NDVI mapping and decide on pesticide contamination in food (fruit and vegetable used as sample example in research)

Method Details & Experiment

The Light spectral analysis module of our solution based on scientific known principle of adsorption of light spectrum by inorganic matter. Normalized difference vegetation index (NDVI) method which is also known scientific method and is used as a dimensionless index that describes the difference between visible and near-infrared reflectance of vegetation cover and can be used to estimate the density of green on an area of land (Weier and Herring, 2000) is also used in our experiment with customisation to detect inorganic content in fruit. Our Light spectrum-based method makes use of a regression model. The model is based on a customized equation of NDVI and is used to measure reflectance data of Near Infra-Red (NIR) and Red Green and Blue (RGB)

Light after passing through fruit' region of interest to determine probability of pesticide residue above MRL. The model runs with clear differentiation by NIR, RED, Blue spectrum with output calculated by a customized formula instead of standard NDVI formula or other variation. The customized NDVI formula uses blue light spectrum also along with red and Infrared spectrum as it increases the accuracy of pesticide detection with respect to standard NDVI formula as established in repetitive simulation runs with known and test fruit sample.

Figure 5 below displays Light Spectrum method used in our experiment

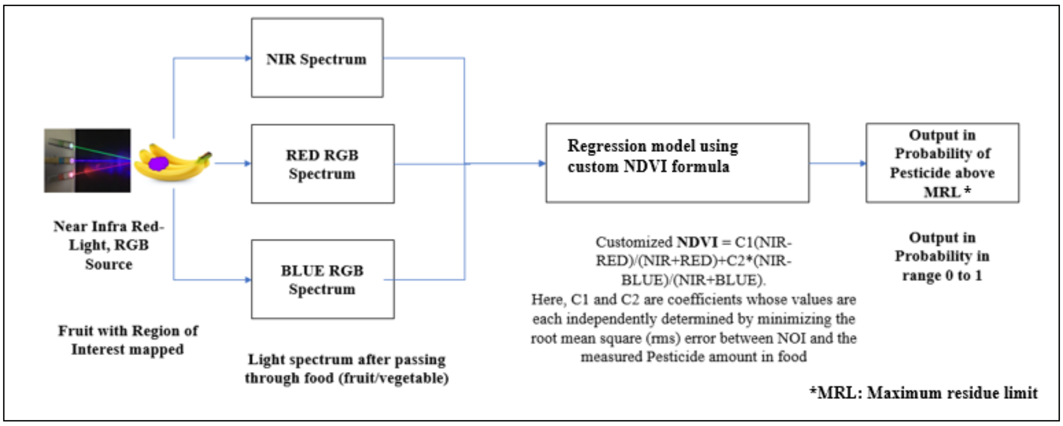

Figure 5. Block Diagram for Light Spectrum method of pesticide determination

This method uses Laser induced Near Infra-Red (NIR) with 940 nanometre (nm) and RGB light spectrum (400 nm to 600 nm) using voltage source of 5 volt. This is passed through the sample food (fruit, vegetable etc.) placed in static container attachable to the IOT device or in moving conveyor belt. Near Infra-red light and visible RGB light source is used to send Near Infra-red and RGB light spectrum to the food sample.

The Near Infra-red spectrum flux after passing through fruit is captured by an optical sensor – Near Infrared receiver and Light dependent resistor (LDR) sensor. The associated voltage for the visible RGB light spectrum is captured by the LDR sensor. In this experiment, the sensors are controlled by a microcontroller – ATmega328 integrated with Arduino UNO R3 IOT device. Sensor RFID tag chip – MLX90129 stores the sensor data. Near Infra-Red (NIR) and RGB light spectrum when passes through a sample food (fruit, vegetable etc.) having pesticide, then due to abiotic molecular excitation by absorption of light energy results in various organic reactions or reactive oxygen species such as Hydroxide molecules. A part of its light spectrum is absorbed by the pesticide residue in food (fruit, vegetables etc.).

The IOT Pesticide determination engine makes use of an intelligent model which uses data from the optical reflectance of laser induced Near Infrared (NIR) and Red Green Blue (RGB) light from food (fruit and vegetables). It uses an automated program to mark region of interest in food (fruit/vegetables) to achieve high accuracy of reflectance of NIR and RGB light spectrum. When the light spectrum passes through the sample food (fruit, vegetable etc.) having pesticide, a part of its' light spectrum is adsorbed by the pesticide residue in food (fruit, vegetables etc.). Once the laser infused light spectrum passes through region of interest in the food, it is captured by Infrared and RGB receiver sensor, and the data so captured is then sent to the model for analysis.

The intelligent model takes the reflectance data as input and using the regression formula automatically determines the probability of pesticide residue content in food.

Customised NDVI =

$$C1^* (NIR - RED) / (NIR + RED) + C2^* (NIR - BLUE) / (NIR + BLUE)$$

Here, C1 and C2 are coefficients whose values are each independently determined by minimizing the root mean square (RMS) error(standard conventional method to measure model accuracy) between customized NDVI and the measured Pesticide amount in food (fruit, vegetable etc.). NIR is Near-Infra-red spectrum and RED, BLUE are RGB Red and Blue Light spectrum which passes through fruit and captured by a receiver sensor.

Result & Analysis

Table 1 shows Mean Value of NDVI and Relative % Deviation using the mentioned Light spectrum method for sample

i) injected with pesticide (Chlorpyrifos or Malathion),
ii) fruit sample from organic farm and
iii) sample from market which has fruit produced from farm with predominant practice of spraying pesticides.

Table 1 and Figure 6 result shows that the market fruit sample of banana have NDVI value mean .76 which is near to NDVI mean value (as .79) of fruit injected with pesticide (Chlorpyrifos or Malathion) and much higher than fruit grown in organic farm(mean NDVI=.61). The result signifies that fruit collected from the market for the experiment has higher pesticide residue limit than fruit grown from an organic farm.

Table 1. Mean Value of NDVI and Relative % Deviation using Light spectrum method

Sample type	Number of samples analysed	Mean value of NDVI in Light spectrum method			Relative % deviation	
		Organic samples (Pesticide free)	Sample injected with pesticide	Market sample	Sample injected with pesticide	Market sample
Banana	10	0.61	0.79	0.76	7.1	6.6
Apple	10	0.68	0.86	0.84	8.5	9.1

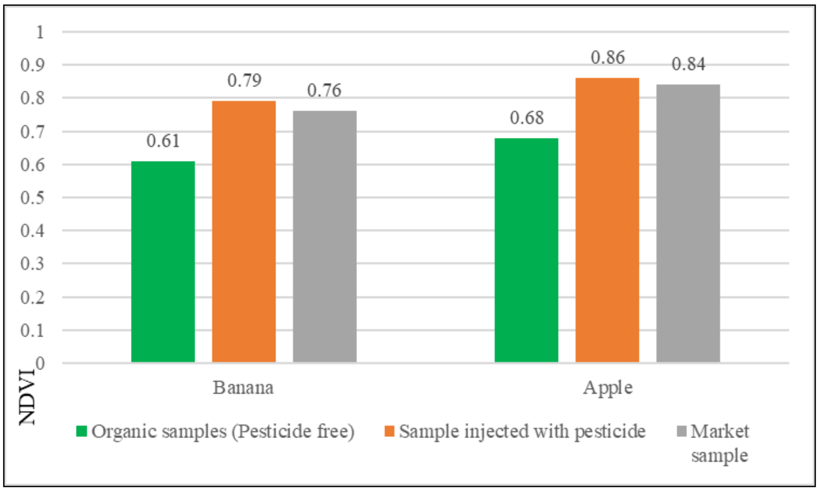

Figure 6. Pesticide detection with Mean Value of NDVI using Light spectrum method

The below graph (Figure 7) that is created by using a statistical method depicts fruit injected with pesticide have Customized NDVI in range .2 to .6 mm and fruit from organic farm (without pesticide) have customized NDVI in range .7 to .8. mm.

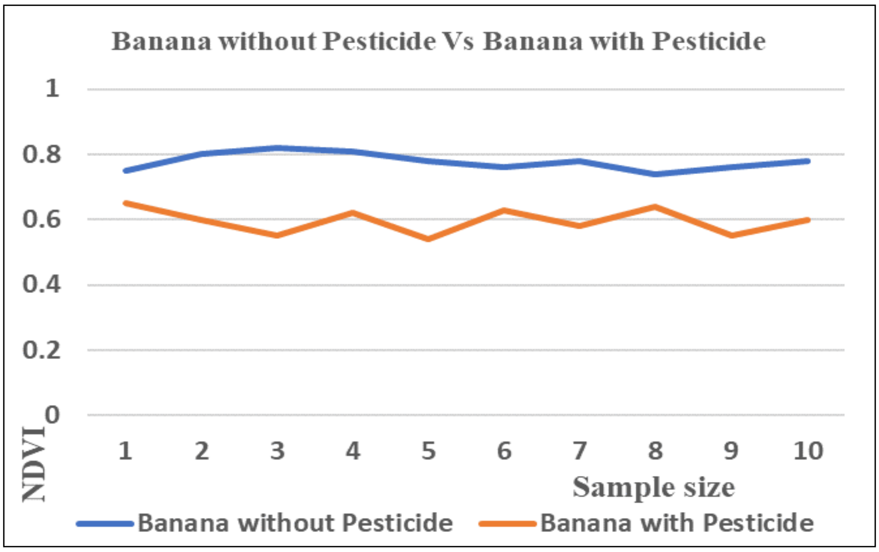

Figure 7. NDVI Graph output of model for banana with or without Pesticide

3.4. Method 5: Gas Sensitivity Method for Pesticide Testing

Method Details & Experiment

In our experiment, GAS sensor-based method is used to detect pesticide residue in terms of relative percentage variation of the gas (ΔG%) parameters in a fruit sample (here, banana). The method uses intelligent regression of output data from GAS Sensors (MQ3, MQ135, TGS822 and HS135), the output of which as (ΔG%) tends to cross threshold in case the fruit sample contains pesticide above prescribed residue limit as shown in Figure 8.

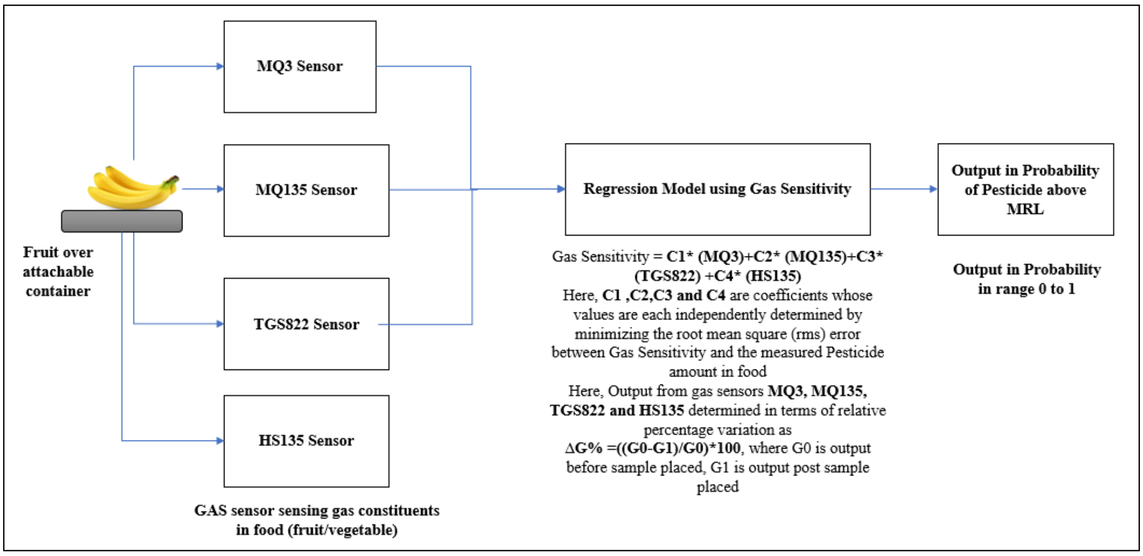

Figure 8. Block Diagram for GAS Sensitivity based method of pesticide determination

Result & Analysis

Table 2 shows Mean Value of ΔG% (% change in Gas sensor sensitivity output) for banana fruit and relative % deviation using the Gas sensitivity method for sample

i) injected with pesticide (Chlorpyrifos or Malathion),
ii) fruit sample from organic farm and
iii) sample from market which has fruit produced from farm with predominant practice of spraying pesticides. Table 2 and Figure 9 result shows that the market fruit sample of banana has % change in Gas sensor sensitivity output value, which is relatively nearer to %change in Gas sensor sensitivity output mean value of fruit injected with pesticide (Chlorpyrifos or Malathion) and much higher than fruit grown on an organic farm. The result signifies that fruit collected from the market for the experiment has higher pesticide residue limit than fruit grown from an organic farm.

Based on statistical analysis as displayed in Figure 10 and Table 2, the relative percentage variation of the gas output ΔG% result for fruit with chlorpyrifos is found to

i) deviate 20% or more for MQ3 Gas sensor which measures Alcohol, Ethanol, Methane etc.,
ii) deviate ~15% or more for MQ135 Gas sensor which measure Ammonia, Benzene etc.,
iii) deviate ~25% or more for TSG822 Gas sensor which measures Organic Solvent Vapours and Carbon Monoxide and
iv) deviate ~23% or more for Chlorpyrifos for HS135 Gas sensor which measure CO_2, SO_2 and Isobutane.

The data has been collected post thorough fruit testing on the IOT device.

Table 2: Gas sensitivity mean value and deviation % result on pesticide testing for banana

Sensor type	Number of reading analysed	Mean value of ΔG% for fruit with pesticide in Gas sensitivity method			Relative % deviation	
		Pesticide free Samples	Pesticide containing Samples	Market sample	Pesticide containing samples	Market sample
MQ3	110	6	20	19	6.1	5.6
MQ135	110	4	15	13	7.3	7.7
TGS822	110	10	25	26	5.4	5.9
HS135	110	8	23	21	7.8	8.6

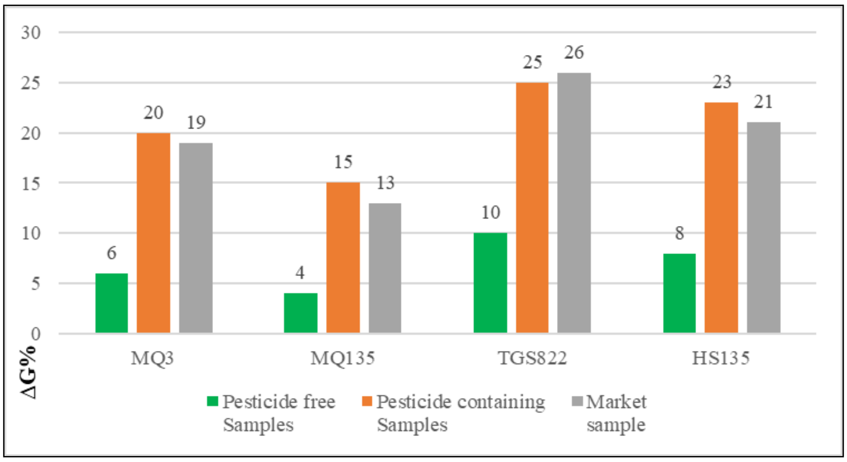

Figure 9: Pesticide detection with Mean Value of Δ**G%** using Gas sensitivity method

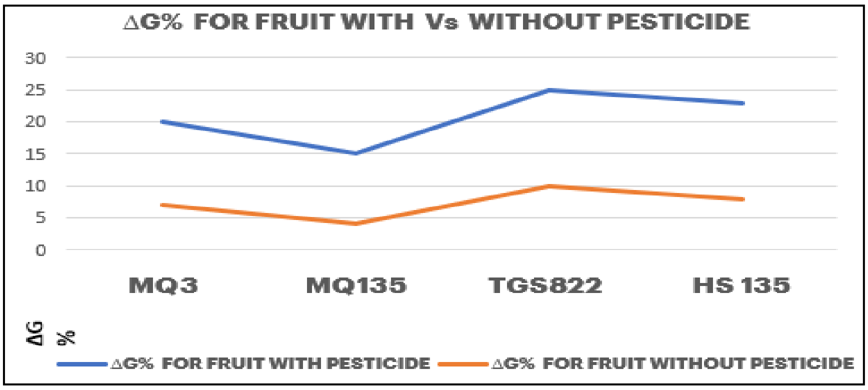

Figure 10. GAS sensitivity output of model with vs without pesticide residue above MRL

3.5. Method 6,7: Moisture Based & Gas Sensitivity Based Method for Freshness Testing

Method Details & Experiment

In our experiment, method 6: Moisture-based method on food freshness detection uses conventional scientific principle that changes in moisture content in fruit can be correlated with freshness in fruit and vegetables. Deviations from the optimal moisture content in fruit and vegetables can severely impact numerous qualities of the food product and safety.

Excess moisture in a food product can lead to an increase in the rate of increase in microbial growth which can decrease the length of time the food can stay fresh to be consumed. Effective and quicker moisture content analysis in food can serve to protect farmers and organizations profits by ensuring product consistency and safety, minimizing waste and at the same time reducing health hazard for end consumers.

In our experiment, method 7: Gas sensitivity based method on food freshness detection uses conventional scientific principle that the production of methane (CH4), carbon monoxide (CO), ethylene gas (C2H4) by fruit (banana here) increases with time and crosses certain threshold value when fruit is rotten /ripen to a certain degree

Result & Analysis

Based on statistical derivation, it is found in our experiment of method 7, have reduction in quantity of Moisture/Humidity below ~10 % threshold, in case of fruit sample is not fresh

Based on statistical derivation, it is found in our experiment of method 8 which is gas sensitivity method that fruits which are not fresh to a certain degree will have concentrations of gas such as Ethyl alcohol, greater than threshold such as 400 µ g/L in MQ3 sensor and ~0.07 d−1 (methane production rate constant).

3.6. Method 8,9,10: Custom Feature Engineering & Image (Thermal, Rgb) Processing

Method Details & Experiment

In our experiment, the images of fruit sample as shown in Figure 4, once uploaded into a virtual machine of the cloud (here AWS), goes through custom feature engineering and image classification algorithm processing. For our experiment, for all the 3 scenarios such as

i) fruit with pesticide contamination but fresh,
ii) fruit without pesticide but not fresh,
iii) fruits that are not pesticide contaminated and are fresh.

The machine learning classification algorithm of convolutional neural network (CNN) runs on the image pixel data and provides output in probability of food testing result. The output probability is sent to decision making model which also consider probability result generated by IOT layer and generating final decision on ‘Pass’ or ‘Fail’ on food testing.

The solution proposes custom feature engineering as shown in Figure 11, which makes use of custom knowledge metadata of features of interest for multiple varieties of fruit and vegetables. The custom feature engineering method then makes use of a statistical method of randomized Hough transformation and Support Vector Machine (SVM)- Recursive Feature Elimination (RFE) classifier to initialize ranking of the features weights for a given fruit image uploaded and thereby extract important features such as texture, colour, shape etc. The important features selected are only passed to subsequent image classification step to improve the accuracy of prediction.

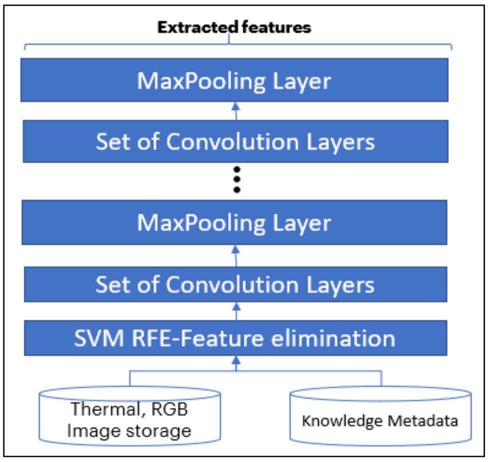

Figure 11. Custom feature engineering method

Step 1: Feature Engineering using Custom Randomized Hough Transform & Svm Rfe Method

In our experiment, our solution uses a randomized Hough transform based (RHT) method for feature engineering. We defined knowledge metadata of important features in each set of images. The method is automatically extracting important features such as texture, colour, shape etc from raw images.

The algorithm using RHT helps to detect region of interest (ROI) curves and hence avoid conducting the computationally expensive voting process of each non-zero pixel in the image. The algorithm improves model run time efficiency and reduces the storage requirement in comparison to the original algorithm without any custom feature selection.

Reverter et al. [20] recommended a method which make use of the kernel principal component analysis (KPCA) space to represent the direction of maximum growth locally for each of given variable and find region of interest, Sanz, H. [21] proposed used of SVM-RFE for selection and visualization of the most relevant features through non-linear kernels.

In our experiment we have done further research on Reverter et al. [20] and Sanz, H. [21] study and created a custom program for region of interest selection and important feature extraction of fruit images being tested. The method in our experiment fits the SVM graph and plot the input observations with respect to the two first components of the KPCA. The difference for each feature variable between the average angle and the median of all given variables average angle is being calculated. The variable which is closest to the median is being classified as less relevant based on ranking of feature variables.

To achieve this, the method automatically performs the feature extraction method as displayed in Figure 12 using SVM-recursive feature elimination (RFE) to select only those features in the training dataset that are most relevant in predicting the target variable which based on converging and diverging mapping. The method in our experiment helped to reduce classification computation time by ~20%. The result shows the use of SVM RFE results in better performance and accuracy rate.

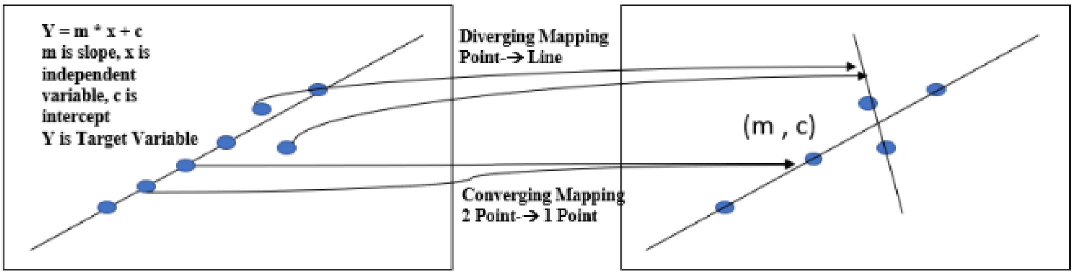

Figure 12. SVM-recursive feature elimination (RFE)

Step 2: Sequence of Convolution & Maxpooling Layer of Food Image (Thermal, Rgb) Processing

Post feature engineering, Convolutional neural network (CNN) algorithm with series of Convolution layers and Maxpooling layers as displayed in Figure 11 and Figure 13 is used to classify food (fruit/vegetable) thermal images. It classifies and calculates accuracy probability of the food as ‘Pass’ or ‘Fail’ in Pesticide and freshness test with a high degree of certainty which is captured in subsequent section.

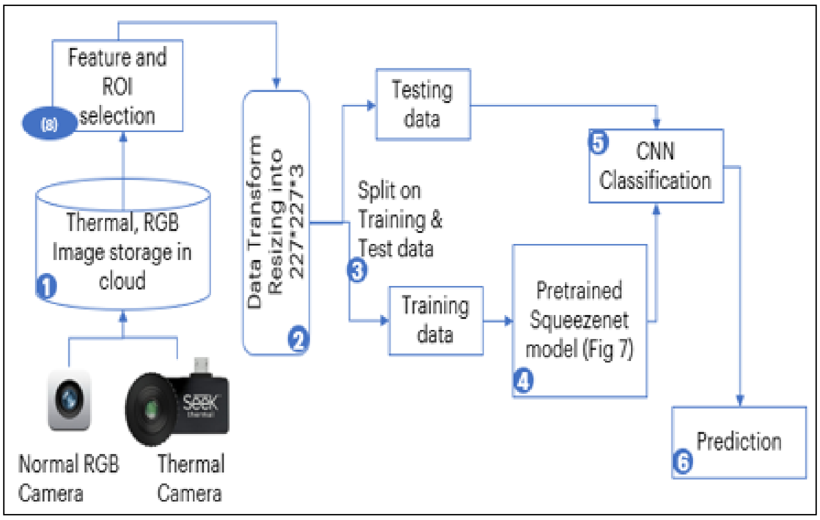

Figure 13. Feature and Region of Interest Selection Methods in Pre-processing of Image Classification

Image processing for pesticide detection in this solution uses sigmoid activation function which has a characteristic S-shaped curve to map nonlinearity in input data into output classification of food testing. Sigmoid functions map the entire number line into a small range such as between 0 and 1, which is used to convert a real value into one that can be interpreted as an accuracy probability.

We have used a customized sigmoid function with required tuning hyper parameters as the last layer to train a deep learning model which can serve to convert the model's output into higher accuracy probability score, which can be easier to determine whether a fruit is fresh or not and whether it has pesticide on it or not. The logistic sigmoid function is defined as follows:

$S(x) = \frac{1}{1+e^{-x}}$, Where, ***x*** is any real-valued input. The logistic function in our model takes any real-valued input, and outputs a value between zero and one as shown in Figure 14.

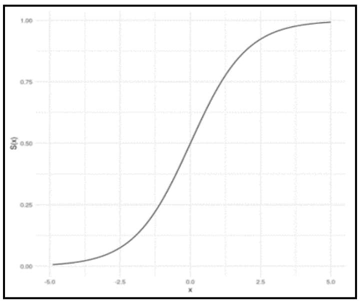

Figure 14. Logistic Sigmoid Function as activation function to the model

Result & Analysis

The classification algorithm in our experiment converts real-valued inputs vectors of food (fruits, vegetable) into classified output of a probability percentage that a fruit/vegetable has a pesticide contamination on it above the maximum residue limit (MRL) or is not fresh. The machine learning algorithm runs on the image data and a decision on pass or fail is sent via API call to the frontend web UI.

Pesticide testing result using image processing:

Our ML layer has predicted the correct result with ~70%-85% accuracy* as measured against set of train and test data of fruits for pesticide testing for sample

i) fruit injected with pesticide (Chlorpyrifos or Malathion),
ii) fruit sample from organic farm

Freshness testing result using image processing:

Our ML layer has predicted the correct result with ~95%-98% accuracy* as measured against set of train and test data of fruits for pesticide testing for sample

i) fruit selected as rotten,
ii) fruit sample which is fresh from

*The above mention accuracy is achieved on repeative run of the model (more than 15 times).

3.7. Method 11,12,13,14: IoT & Ml Layer Decision Probability

Result & Analysis

In our experiment, method 11,12 provides IOT Layer decision value (in probability) for freshness and pesticide detection respectively. Method 13,14 provides Image processing layer decision value (in probability) for freshness and pesticide detection respectively. The probability value lies in between 0 and 1 where 1 means 100% confidence the food passes the required threshold in testing (For Pesticide contamination or Freshness food testing).

In our experiment, it is found the confidence percentage output from IOT layer processing and image layer processing, varies with each other by +- 10% range for ~95% trial runs.

3.8. Method 15, 16: Intelligent Decision-Making Method & Result Display

Method Details & Experiment

The output from IOT layer and ML layer is passed as a probability percentage into Intelligent decision making layer. decision-making layer as shown in Figure 15. The decision-making layer makes use of ensemble method and takes into consideration the output from both IOT and ML and intelligently predicts if the food (fruit / vegetable) is fresh and safe for consumption based on the pesticide limit using a Regression algorithm based on below equation

$$\begin{bmatrix} x1 & x2 & x3 & x4 \end{bmatrix} \begin{bmatrix} a1 \\ a2 \\ a3 \\ a4 \end{bmatrix} = \begin{bmatrix} x1a1 \\ x2a2 \\ x3a3 \\ x4a4 \end{bmatrix}$$

Here, 4 input parameters are used, the variables x_1, x_2, x_3, x_4 constitute of input features. In our experiment, 4 input features are probability percentage output from

i. IOT decision method on freshness

ii. IOT decision method on pesticide
iii. ML decision method on freshness
iv. ML decision method on pesticide

Output= $A_1x_1+A_2x_2+A_3x_3+A_4x_4$

Where, A_1, A_2, A_3 & A_4 are coefficient of weightage of Output (in probability) from Pesticide, Freshness determination IOT and ML model respectively. Here a coefficient with higher weightage is automatically assigned to the IOT model than CNN model output.

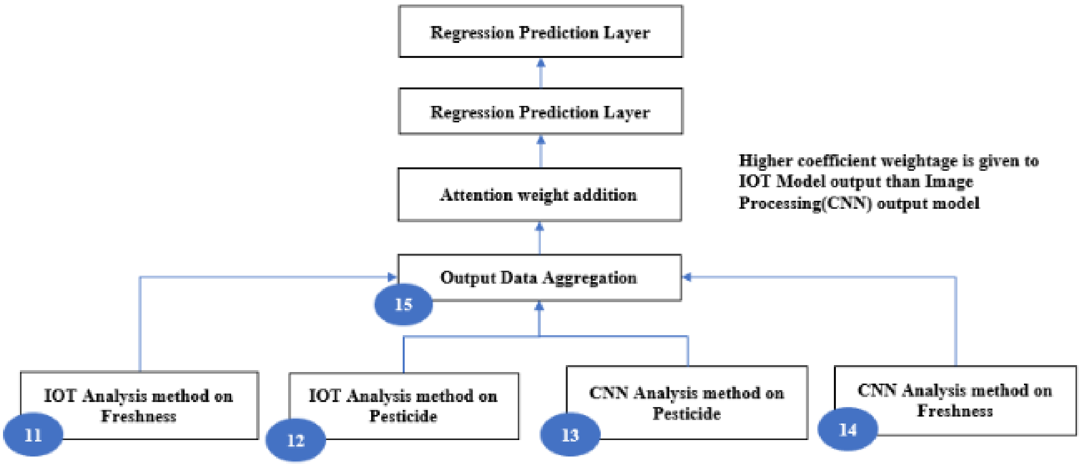

Figure 15. Intelligent Decision-Making Layer Diagram

Result & Analysis

The decision-making model then predicts the final confidence percentage of the food (fruit here) having pesticide contamination or food spoilage. If the confidence percentage in the final decision-making layer is higher than the threshold then it displays as 'Pass' or 'Fail' in dashboard of mobile/Web UI as shown in Figure 16. The display method notifies the IOT edge device (used for food testing) using 'Red led' light and 'buzzer alarm' in case of failure and 'Green led' light in case the food passes food testing (in both pesticide contamination and freshness test) as shown in Figure 17.

The solution has accuracy ~95% in freshness detection and has accuracy in the range of ~65% to ~85% for pesticide contamination detection in fruit banana and apple used in the experiment.

Figure 16 shows overall decision result as 'PASS' or 'FAIL' in food testing in user interface of desktop/mobile

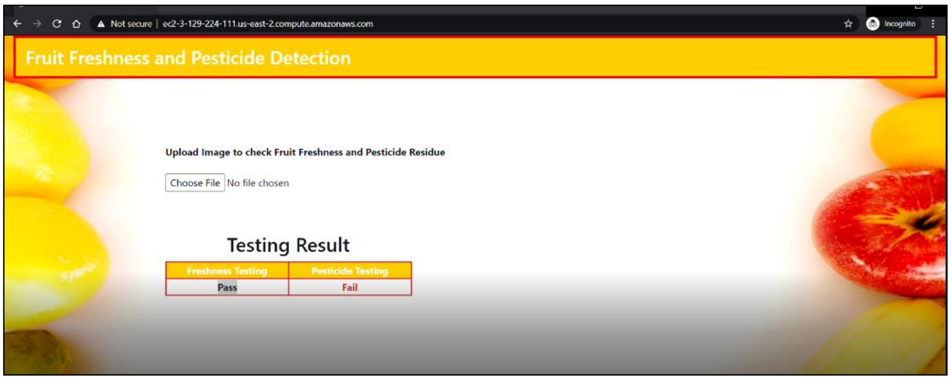

Figure 16. Web UI dashboard of Fruit testing result on Pesticide and Freshness testing

Figure 17 shows overall decision result as 'RED led' light display with 'buzzer sound' or 'GREEN led' and no 'buzzer sound' in food testing in edge IOT device used for food testing

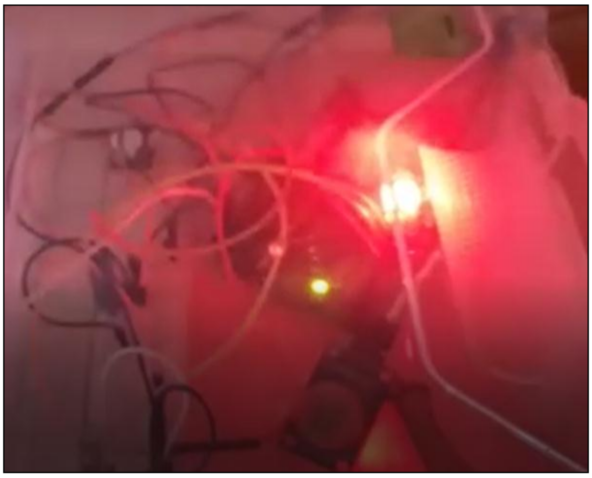

Figure 17. IOT device led display of Fruit testing result on Pesticide and Freshness testing

4. Hosting ,Pre- Requisites, Limitation & Business Outcome

4.1. Hosting

The core ML and IOT solution code for proof of concept was hosted in AWS cloud but the code can be hosted on edge/on premise along with cloud. The solution can also be integrated with a mobile App/ Web UI. This can be integrated with low cost Electro-Optical-Gas sensors and image processing (CNN algorithm) model in edge device or hosted in cloud using API.

4.2. Pre-Requisites

Enough training data: For good accuracy, the model requires minimum more than 1000 training data of fresh, rotten fruit images and hyperspectral images of fruit with and without pesticide.
Sensor calibration: Sensor calibration also needs to be done to remove any bias to get accurate reading.

4.3. Limitations

The success of this innovation is dependent on the availability of training data as mentioned in the pre-requisites.

4.4. Business Outcomes

This solution will:

- Assist Sellers (Wholesalers, Retailers) to segregate food (fruits, vegetables) above or below pesticide maximum residue limit (MRL) and freshness gradation
- Empower consumers with information on pesticide residue and freshness to enable healthy eating habits by purchasing food with the testing result displayed with portable low-cost non-destructive solution.
- The smart and low-cost product solution will enable all stakeholders (government, sellers, consumers) to comprehensively monitor the food testing results, and take real-time decisions which in turn will help to reduce health hazards.
- Reduce mass food spoilage with early and accurate detection of spoiled foods.

5. CONCLUSION

The paper attempts to show innovation that provides an intelligent, quicker, and accurate food testing solution for detecting pesticide residue and freshness using innovative non-destructive methods. This experiment involved a few selected fruit categories, but the solution can be scaled to other food categories such as vegetables and grains. The solution has good accuracy (~95%) in freshness detection, but for pesticide detection the accuracy lies in the range of ~65% to ~85%, which can be improved further in the future by making use of higher sensitivity sensors. In addition, the future sensors should cover more pesticide classes such as organonitrogen, which is not covered in this experiment. The solution 'eJagruk' can be deployed in a phased manner to different segment of the users such as food aggregators, retailers, whole sellers, food processing industry and common men.

This innovation solution will empower humans to decide what to eat and what not. The practice will ensure a healthy world and will discourage malpractices in food production.

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DISCLAIMER

ABBREVIATION

NDVI: Normalized difference vegetation index
RGB: Red, Green and Blue light spectrum
MRL: Maximum residue limit
KPCA: Kernel principal component analysis
RFE: Recursive Feature Elimination
SVM: Support vector machines
CNN: Convolutional neural network
ML: Machine Learning
IOT: Internet of Things
NIR: Near Infra-Red
GC: Gas chromatography
LC-MS: Liquid chromatography–Mass spectrometry
HPLC: High performance liquid chromatography
ATR: Attenuated total internal reflection
FT: Fourier transform
PIC: Programmable Interface Computers
SD card: Secure digital card
IDE: Integrated development environment

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