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Fruit Adulteration Detection Utilizing Machine Learning Methods

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Abstract

A device utilizing Internet of Things (IoT) technology was developed for the identification of fruit adulteration through machine learning methods, specifically targeting formalin content assessment. The identification of the fruits based on their extracted traits has been accomplished using a variety of machine learning techniques. The formalin concentration can be detected as an estimate of the generated voltage of any fruit via an Arduino Uno board 3 and a volatile compound sensor. The approach we use can distinguish between organically formed and chemically added formalin utilizing machine learning methods that precisely predict the ideal formalin content at any temperature. The primary aim of this system is to supplant traditional inspection approaches. This approach involves capturing images using cameras installed on moving belt conveyors. By analyzing the picture pixels, key characteristics of fruits are used to detect contaminated ones. Subsequently, the fruits are sorted based on their size and color.

Keywords: IoT, formalin, machine learning, Arduino, Methods

INTRODUCTION

Any fruit substance consumed is done so to receive the nutrient benefits. Since the fruits go through numerous stages of production, processing, and distribution steps, the amount of nutrition has declined. The concept of adulteration is commonly employed to improve the preservation and visual appeal of fruits. Fruit adulteration is the process of altering the quality or nature of fruit by introducing adulterants or removing necessary components. One of the adulterants may be a foreign or subpar chemical that is found in fruit. To improve the fruit's appearance or storage qualities, a small number of chemicals that are not nutritionally beneficial are purposefully added to the fruit during the adulteration process.

Most instances of fruit and vegetable adulteration result from the utilization of the harmful chemical known as formalin. An aqueous, colorless solution of formaldehyde is called formalin and is used to preserve the biological material. This substance is used to stop the rotting of corpses. This attribute is utilized to counteract decay. Merchants use formalin as a preservative to extend the shelf life of fruits and vegetables, simultaneously enhancing their appearance. Abdu's Sobhan, the secretary of SEM, discovered that 115 samples of mangoes and other fruits were formalin-treated after being obtained from more than 50 organic stores that advertise chemical-free produce. India stands as an agricultural nation, generating a diverse range of fruits and vegetables. In regards to fruit production, India remains second next to China. In India, all pre- and postharvest procedures are carried out manually

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with the assistance of the manpower. Automation must be implemented in the agricultural industry to provide precise outcomes because traditional approaches take an extended amount of time and are inefficient. Following the harvest phase, fruits undergo sorting and grading. This involves categorizing fruits based on various quality criteria. The characteristics fulfill both internal and external quality prerequisites. Internal quality characteristics include taste, sweetness, flavor, fragrance, nutrients, and carbohydrates present in fruits. The exterior quality factors are texture, shape, color, size, and volume.

Adulteration does not invariably result in significant negative health effects. In the present context, identifying fruit adulteration using Arduino can have consequences. The chemical is exceedingly hazardous, though, and is one of the simple strategies that present outcomes by calculating the fruit's formalin content.

It is possibly deadly if you ingest 30 cc of formalin which includes 37% formaldehyde.

LITERATURE REVIEW

Suprith Kaur, Jasmine Gill, and Akshay Girdhar, Sringer Nature Singapour 2018 [1]. This study proposes a computer vision and image processing-based system for grading and sorting vegetables. Tomatoes have been used as an example vegetable for this investigation. 53 images in total were captured using the user's camera setup. The vegetable was then separated from the backdrop using Otsu's method of segmentation. The resulting segmented images were then utilized to extract color and texture elements. Finally, a back propagation neural network was used for sorting and grading. The suggested solution outperformed the current system and had a 92% accuracy rate.

Deepika Sharma, Sharad O. Sawant, 2017 [2], The image processing system developed the grain quality detection technique. They have suggested a system in this essay for determining the food quality. The grain samples are initially transported on the conveyor belt, and after that, a camera randomly takes photos of the grains. Through MATLAB, the image processing technique is applied to the grain samples. Color, shape, and size have all been used as criteria for categorization.

Heena Shakir, Mohamad Anzhar Aalam, and Zhahida Parveen in 2017 [3]. They developed a system that uses optical and image processing to assess the quality of rice grains. To identify the chalky area in the rice, an image processing technique using the extended maxima operator is proposed in this study. For classification, they also calculated the size and color of the rice grains. 22 example images of rice grains were used in the experiment to evaluate the suggested methodology and visual inspection was used to confirm the results.

Simati M. Jagdale and Manali R. Satpute, 2016 [4]. The automatic fruit inspection system illustrated in this study collects images from a camera that is mounted on a conveyor belt. The essential fruit traits, such as size, color, and texture, are consequently extracted by image processing. Blob detection is used to identify fruit that is infected, thresholding is used to identify hue and a binary picture of a tomato is used to identify the size. Sorting and grading are done according to size and color respectively.

C.S. Nandi, B. Tubu, and C. Koley 2014 [5] An IEE Transactions study on a machine vision-driven system to predict the ripeness of harvested mangoes for sorting purposes. This paper processing machine vision system is appropriate for categorizing mangoes based on the day after harvest that they are still edible. The proposed machine vision-based system's overall performance was discovered to be superior to that of human experts.

Prof. Kapale N.D. [6] The most recent advancements in autonomous vision-based technologies are presented in this paper. Deployment of this technology across agriculture and the fruit industry is booming. For fruit sorting, grading, and defective fruit identification, an automated method is available.

Nandhini P. and Dr. J. Jaya [7] authored a paper titled 'Utilizing Computer Vision System for Food Quality Assessment through Image Segmentation: As a result, this study offers several methods for locating flaws in food products using computer vision systems. Picture acquisition, Preprocessing, image segmentation, feature recognition, and classification are some of the phases in a computer vision system.

Theofill, Franz Christian Bato, and Crystalynne D. Cortez International Journal of Information and Electronics Engineering, Vol5, No.5, September 2015 [8], "Development of Formaldehyde Detector," by Jake G. Bautista, Julius Mel G. Cantor, Clestino L. Gandionco, and Stephany P. Reyes. The study involved the creation of a detector that can identify formaldehyde levels in air measured in parts per million (ppm). Real-time data was stored in the prototype using storage device (SD) technology. The study's goal was to build and create a system that can measure formaldehyde content and tell if the reading is at or above the allowed threshold. To assess the precision of the system, a 5ml quantity of formaldehyde was introduced into a 5-litre container. The employment of a Machine Learning Approach in the Food and Formalin Detection System by Kanij Tabassum, Afsana A. Memi, and Nasrin.

Sultana, Ahmed W. Reza, and Surajit D. Barman, October 2019, Volume 9, Issue 5 of the International Journal of Machine Learning and Computing [9]. In this study, an innovative and accurate system for distinguishing food and formalin using machine learning is introduced. Numerous approaches to machine learning, such as Naive Bayes, Logistic Regression, Support Vector Machine, and K-NN Classifier, are utilized in creating a prediction model from the simulated dataset. The type of food was determined using conductive characteristics. Using an Arduino Uno and VOC HCHO gas sensor in combination, the system is capable of detecting formalin concentrations between 1 and 50 ppm.

PROPOSED SYSTEM
The manual inspection system is being replaced as the main goal of this system. This aids in speeding up the procedure and boosting accuracy and effectiveness. Our local disc serves as the system's input for the dataset. Then, image processing is implemented to obtain the pertinent fruit traits, such as its dimension and color. Fruit adulteration is identified based on image pixels using the YOLOv3 (you only look once) algorithm, which is more efficient than YOLOv2, and CNN using the technique VGG16: The VGG16 model performs convolution of size 33 (with 64 kernels/output channels) with a stride of 1 and a padding of 1 on an input picture of size 224224 (three color channels). The framework isolates the learning elements and tags to determine if the fruit image has been tampered with. The device will display the amount of formalin present in the fruit if it is adulterated. This model attains a top-5 test accuracy of 92.7% when evaluated on the ImageNet dataset, comprising 14 million images categorized into 1000 classes. The sorting process relies on color distinctions. Moreover, the trained weights will be utilized in the detection process to identify the color of the chemical constituents that have developed within the fruit, manifesting as distinct white layers on the fruit's surface.

By utilizing IoT, we can discover the presence of formalin in can be purchased already constructed or as kits tailored to fruits, a sign that the fruit has been tampered with. Fruit is specific applications considered contaminated and unsafe to eat when formalin is found in it.

METHODOLOGY
Hardware Requirements
1. *Processor:* State-of-the-art i3.
2. *RAM:* 4GB or above.
3. *Storage:* 4GB or higher free drive space/cloud space.

Software Requirements
1. *Programming language*—Python.
2. *Operating system*—Windows 7 and later versions.

3. *PyTorch*—An open-source machine learning library used for applications such as computer vision and natural language processing.
4. Image Processing and Convolution Neural Network associated Python Libraries.
5. Web Framework: Flask.

COMPONENTS USED
- Arduino Uno
- Gas Sensors
- LCD
- Buzzer
- Dc motor
- H-bridge

HARDWARE DESCRIPTION
Using single-board microcontrollers and microcontroller kits, Arduino creates digital gadgets and interactive objects that can sense and control items in both the physical and virtual worlds. Both framework's software and hardware are licensed as open source. The GNU Lesser General Public License (LGPL) governs the use of the project's open-source hardware and software, which are supplied as such. For commercial purposes, you have the option to buy Arduino boards (Figure 1).

Figure 1. Diagrammatic representation of the board.

PIN DESCRIPTION
Table 1 consists of a detailed explanation of the pin category along with their name and the specification which leads to the significant impact.

Table 1. The pin description Arduino Uno board.

Pin Category	Pin Name	Details
Power	Vin, 3.3V, 5V, GND	Vin: Input voltage to Arduino when using an external power source. 5V: Regulated power supply used to power the microcontroller and other components on the board. 3.3V: 3.3V supply generated by the onboard voltage regulator.
Reset	Reset	Resets the microcontroller.
Analog Pins	A0–A5	Used to provide analog input in the range of 0–5V.
Input/Output Pins	Digital Pins 0–13	Can be used as input or output pins.
Serial	0(Rx), 1(Tx)	Used to receive and transmit TTL serial data.
External Interrupts	2, 3	To trigger an interrupt.
PWM	3, 5, 6, 9, 11	Provides 8-bit PWM output.
SPI	10 (SS), 11 (MOSI), 12 (MISO) and 13 (SCK)	Used for SPI communication.
SPI	10 (SS), 11 (MOSI), 12	Used for SPI communication.
Inbuilt LED	13	To turn on the inbuilt LED.
TWI	A4 (SDA), A5 (SCA)	Used for TWI communication.
AREF	AREF	To provide a reference voltage.

LCD OPERATION

LCDs have gained extensive popularity over LEDs (including seven-segment LEDs and other multi-segment LEDs) in recent times. Figure 2 This shift can be attributed to the following reasons:

1. Firstly, there has been a decline in the cost of LCDs.
2. Secondly, LCDs possess the ability to present numerical data, characters, and images, whereas LEDs are limited to displaying a small number of characters and digits.
3. Including a refreshing controller in the LDC, which frees the CPU from having to update the LCD. Conversely, the LED requires refreshing by the CPU (or through an alternative method) to maintain the display of data.
4. Character and graphic programming are simple.
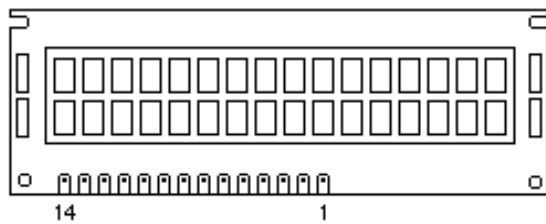
Figure 2. LCD operation.

SENSORS

MQ135 sensor is typically a high-temperature device built to detect formalin Figure 3.

Figure 3. MQ-135 formaldehyde Sensor.

Features
Wide Detecting Scope
- Fast response and high sensitivity
- Stable and long life
- The operating voltage is +5 V
- Detect/Measure NH_3, NOx, alcohol, Benzene, smoke, CO_2, etc.
- Analog output voltage: 0 V to 5 V
- Digital output voltage: 0 V or 5 V
- Can be used as a Digital or analog sensor

HARDWARE

In this category, a detailed blockchain or flow diagram is to be followed which is mentioned (Figure 4).

SOFTWARE

Arduino IDE (Integrated Development Environment) is required to program the Arduino Uno board.

ARDUINO PROGRAMMING

Connect the board to the computer using a USB cable once Arduino IDE has been installed. Open the Arduino IDE now, choose the appropriate board by going to Tools>Boards>Arduino/Genuine Uno, and the appropriate port by going to Tools>Port. The programming language of Arduino Uno is derived from Wiring and is employed for its programming. Select Files>Examples>Basics>Blink to load the sample code and start the Arduino Uno board blinking its built-in LED. Click the "upload" button on the top bar once the example code (as shown below) has been loaded into the IDE. The Arduino's built-in LED should start blinking after the upload is complete. The blinking code example is shown below.
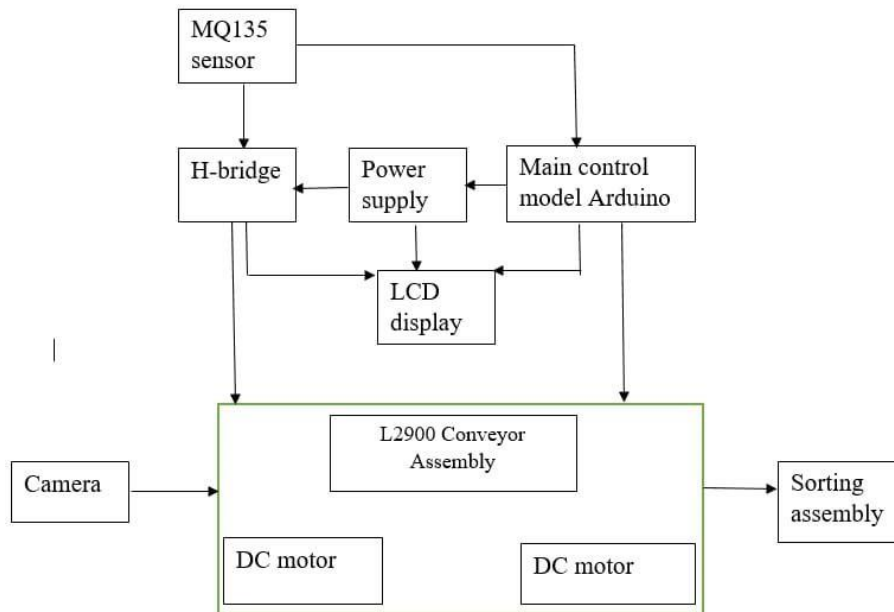
Figure 4. Block Diagram of Formalin Detection System.

```
#include<LiquidCrystal.h> int rs=8, en=9, d4=10, d5=11, d6=12, d7=13;
Liquid Crystal LCD (rs, en, d4, d5, d6, d7);

int motor1=2; int motor2=3; int motor3=5; int motor4=4;

char CH;

//void belt_start();
//void belt_stop();
//void defect_check();

void setup() { Serial.begin(9600);
 lcd.begin(16,2);
 pinMode(motor1,OUTPUT);          pinMode(motor2,OUTPUT);          pinMode(motor3,OUTPUT);
pinMode(motor4,OUTPUT);
```

digitalWrite(motor1,LOW);
digitalWrite(motor2,LOW);
digitalWrite(motor3,LOW);
digitalWrite(motor4,LOW);   lcd.clear();
lcd.setCursor(0,0)   lcd.print("FRUIT");
lcd.setCursor(0,1);
 lcd.print("ADULTERATION");
	// lcd.setCursor(0,0); lcd.print("GOOD FRUIT");
	delay(1000);
	belt_start();
	digitalWrite(motor3,LOW);
	digitalWrite(motor4,LOW);
	} else {
	belt_stop();

```
delay(1000);

}

void loop() { // ppm_check(); belt_start();
}
void belt_start()
{
 digitalWrite(motor1,HIGH);
digitalWrite(motor2,LOW);
 delay(1000); defect_check();
}
void belt_stop()
{
 digitalWrite(motor1,LOW);
digitalWrite(motor2,LOW);
// delay(5000);
 }
void defect_check()
{
Serial.print("C"); belt_stop(); while(1){
if(Serial.available()>0)
{

 CH=Serial.read();         Serial.print(CH);
if(CH=='B')
 {
 lcd.clear();            lcd.setCursor(0,0);
lcd.print("BAD                    FRUIT");
digitalWrite(motor3,LOW);
digitalWrite(motor4,HIGH); delay(200);
 digitalWrite(motor3,LOW);
digitalWrite(motor4,LOW); delay(1000);
 digitalWrite(motor3,HIGH);
digitalWrite(motor4,LOW); delay(200);
 digitalWrite(motor3,LOW);
digitalWrite(motor4,LOW);
 delay(1000); belt_start();
 }
 else if(CH=='G')
 {
 lcd.clear();
```

```
 digitalWrite(motor3,LOW);
digitalWrite(motor4,LOW);
 }

}
 ppm_check();
}
}
void ppm_check()
 {
 int gasval=analogRead(A0); Serial.println(gasval);
 float    ppm=map(gasval,200,1023,0,100);    lcd.clear();
lcd.setCursor(0,0);                     lcd.print("PPM=");
lcd.setCursor(4,0);   lcd.print(ppm);   lcd.setCursor(9,0);
lcd.print("%"); delay(1000);
 if(ppm>20)
 {
 lcd.clear(); lcd.setCursor(0,0);
 lcd.print("MORE FORMILINE"); lcd.setCursor(0,1);
 lcd.print("CONTENT ADDED");
 delay(1000);
 }

}
```

Algorithm Used:
1. Convolutional Neural Network(CNN)
One of the main categories for image affirmation and image portrayals is the convolutional neural framework. CNNs are frequently used in a variety of contexts, including article disclosures, affirmation faces, etc. The neural network with several convolutional layers is depicted in Figure 5 and Figure 6 below. Every data picture will adhere to the process of convolution layers with procedures (Kernel), Pooling, and completely related layers (FC) by applying SoftMax work. With certainty, the likelihood of significant learning CNN models that can be used for training and testing runs somewhere between 0 and 1. The graphic below shows a complete CNN stream that processes an informational image and demands the articles be valued.

The data training in our CNN model must satisfy the following constraints:

There should be no missing values in our dataset.

In the case of an image dataset, all the images must be the same size, as an uneven distribution of image size in our dataset can reduce the effectiveness of our neural network. The dataset must be adequately partitioned into testing and training sets, with neither including any unnecessary data that goes beyond the purview of our model.

Before feeding the images into the convolution layer, the images should be switched to black and white to substantially reduce the model's execution time.

This is because reading images in RGB would require a 3-D NumPy matrix.

Before supplying the database to the neural network, any corrupted or blurred images should also be removed. Let's go right into the regulations for preprocessing information after comprehending them. Functioning of the convolutional neural network.
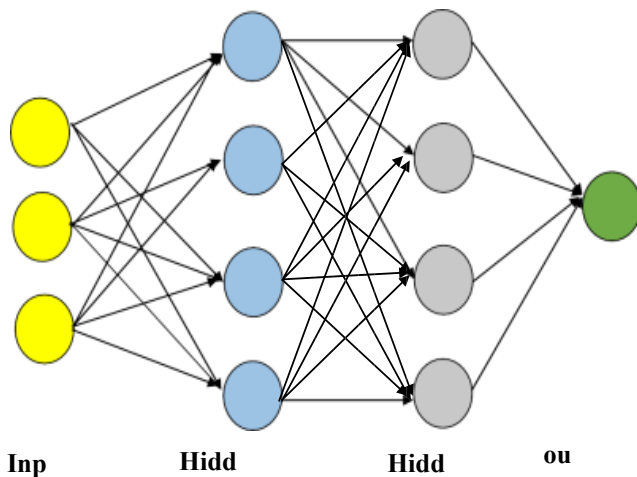

Inp   **Hidd**   **Hidd**   **ou**

Figure 5. Neural network with numerous convolutional layers.
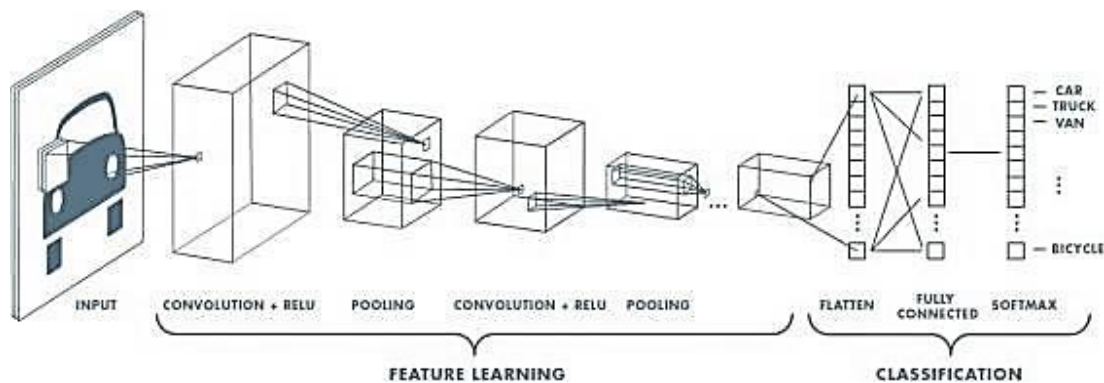
Figure 6. CNN layers.

Convolution Layer
To create a 3x3 matrix for this layer, the entire image requires being scanned for patterns. Kernel pertains to the image's convolved feature matrix (Figure 7).

The weight vector is an acronym given to each element in the kernel.

Pooling Layer
The picture matrix is divided into sets of four distinct, non-overlapping segments during the pooling phase, which follows convolution. Max pooling and average pooling are the two different kinds of pooling. The highest possible value in the selected relative matrix region is provided by max pooling. The mean of all the values in the related matrix region has been generated through average pooling. The pooling layer's main advantage is that it boosts computer performance and diminishes the probability of over-fitting (Figure 8).
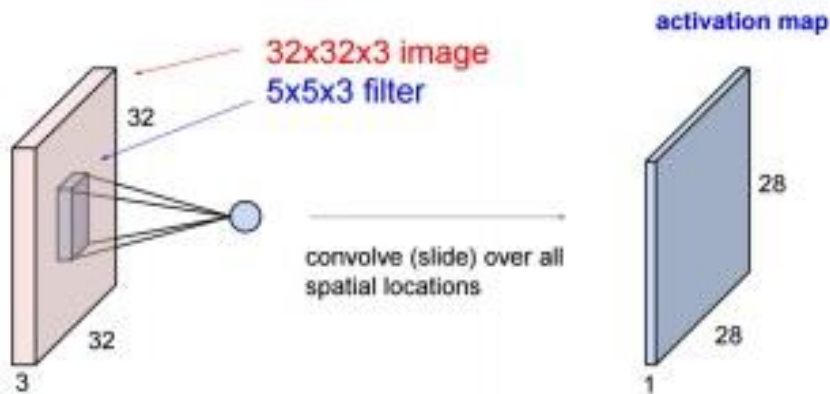
Figure7. Convolutional layer.

Activation Layer

It is the region of convolutional neural networks wherein the parameters undergo normalization; that is, they are fitted within a particular range. ReLU is a commonly used convolutional function that solely accepts inputs that are favorable before rejecting negative values. Low computational expense plays a role (Figure 9).
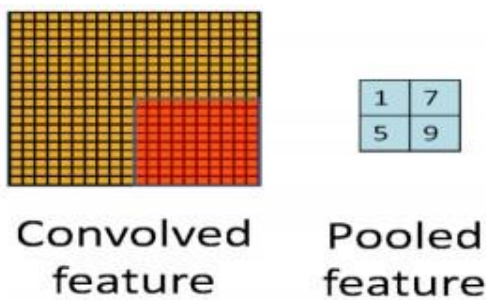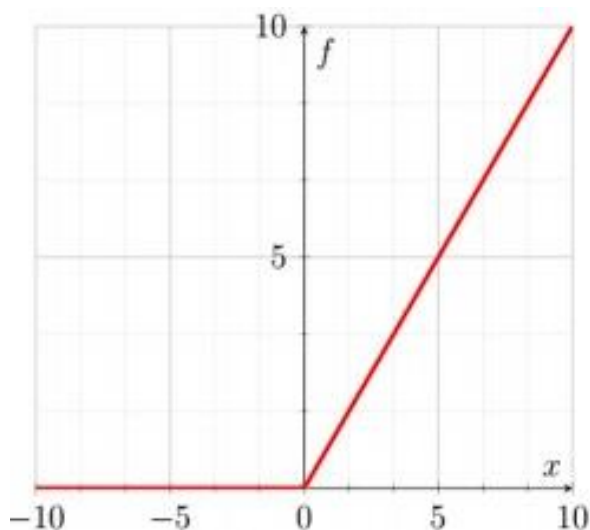

Figure 8. Pooling layer.

Figure 9. ReLU function.

Fully Connected Layer

In this section, comparable characteristics are linked to the designated identifier by comparing them to similar features in the test image. For computational simplicity, identifiers are usually represented as numbers; they will then be transformed into the appropriate strings [10].

Yolo

YOLO predicts the coordinates of the bounding box and likelihoods of classes for these boxes considering the complete image in just a single glance. Yolo's outstanding tempo, which is capable of handling 45 frames per second, is certainly its most significant benefit. Among the three sets of YOLO 3 and 5 iterations, it is evident that the fastest and most precise in detecting small objects is YOLO. The YOLO algorithm, comprising a total of 106 layers, is composed of three distinct layer types. The residual layer that forms when activation is easily passed to the subsequent layer in the neural network. This is the first benefit. The residual configuration involves summing the outputs of layer 1 with those of layer 2. The second layer is dedicated to detection, operating at three distinct scales or stages. Grid sizes are enlarged to facilitate detection. The upsampling layer, which boosts an image's spatial resolution, comes in third. Prior to scaling, the image undergoes an upsampling process. Also, the outcomes of the preceding layer are put together with those of the currently active layer employing a concatenation process. The procedure of addition. Prior layers were already added through adding. The residual layers, detection layers, and upsampling layers are depicted in Figure 10 by the blocks colored pink, orange, and green, respectively. discovery at three different scales is as shown (Figure 10).
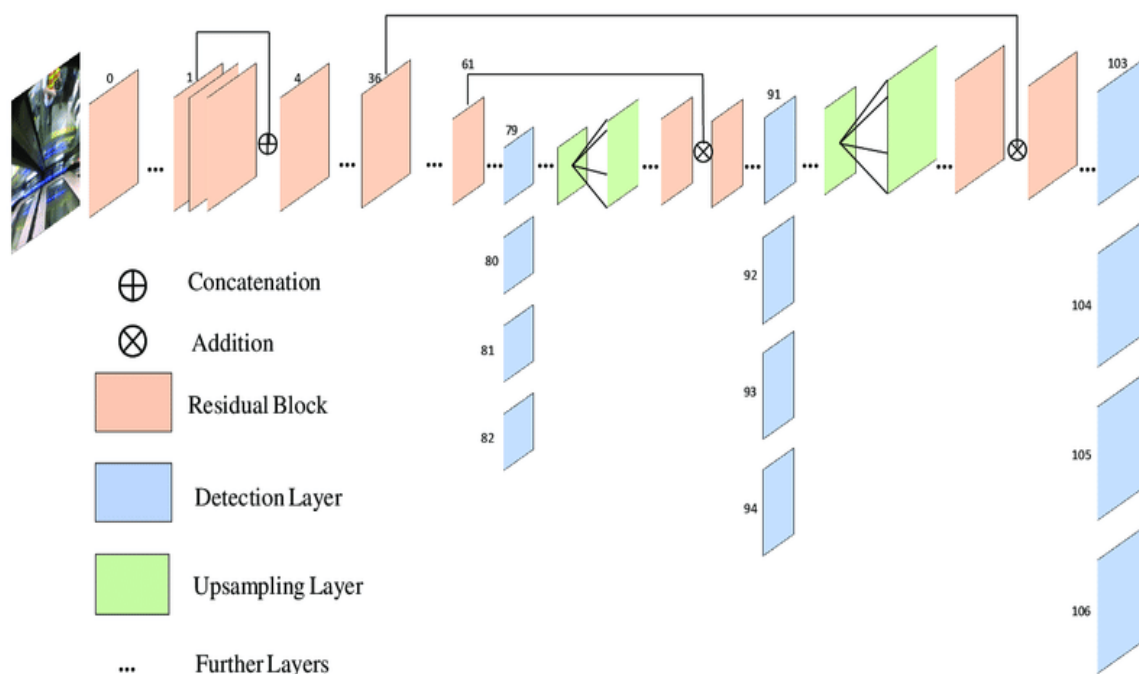

Figure 10. Network Architecture of Yolo-V3.

Use Case Diagram

The use case diagram above depicts the interaction between the user and the system wherein when the user uploads an image, then preprocessing of the image, extracting the ROI is done by the system, and applying the VGG16 algorithm to predict the image (Figure 11).

Sequence Diagram for Preprocessing

The above figure depicts the sequence diagram for preprocessing. An image is uploaded and then the image is opened to undergo preprocessing where the image is resized and noise removal of the image takes place (Figure 12).

Sequence Diagram to Detect Formalin

Figure 13 depicts the continuation of preprocessing to detect formalin where the ROI is extracted from the preprocessed image and the VGG16 algorithm is applied to the extracted image. The trained dataset is loaded and classified output is given which displays the formalin content.
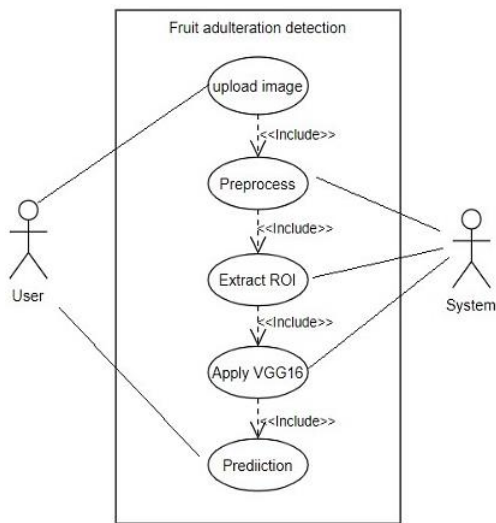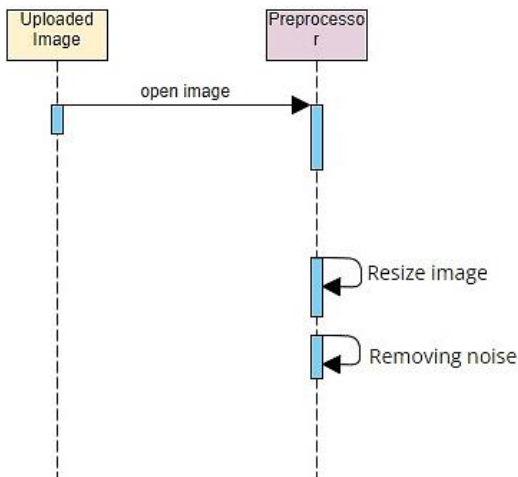
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Figure 11. Use case diagram.

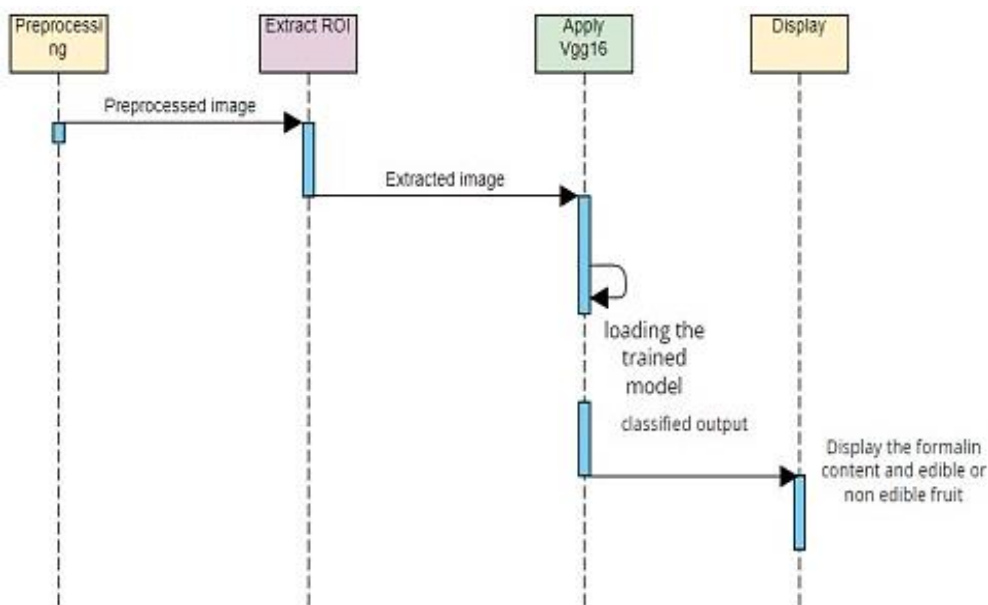**Figure 12.** Sequence diagram for preprocessing.

Figure 13. Sequence diagram to detect formalin.

System Architecture

The above image depicts the system architecture (Figure 14). The input image is selected or real-time captured. The system detects images and undergoes preprocessing, ROI is extracted and the trained model is loaded. In the training phase, the dataset is loaded, trained, validated, and loaded to the system that detects adulteration.
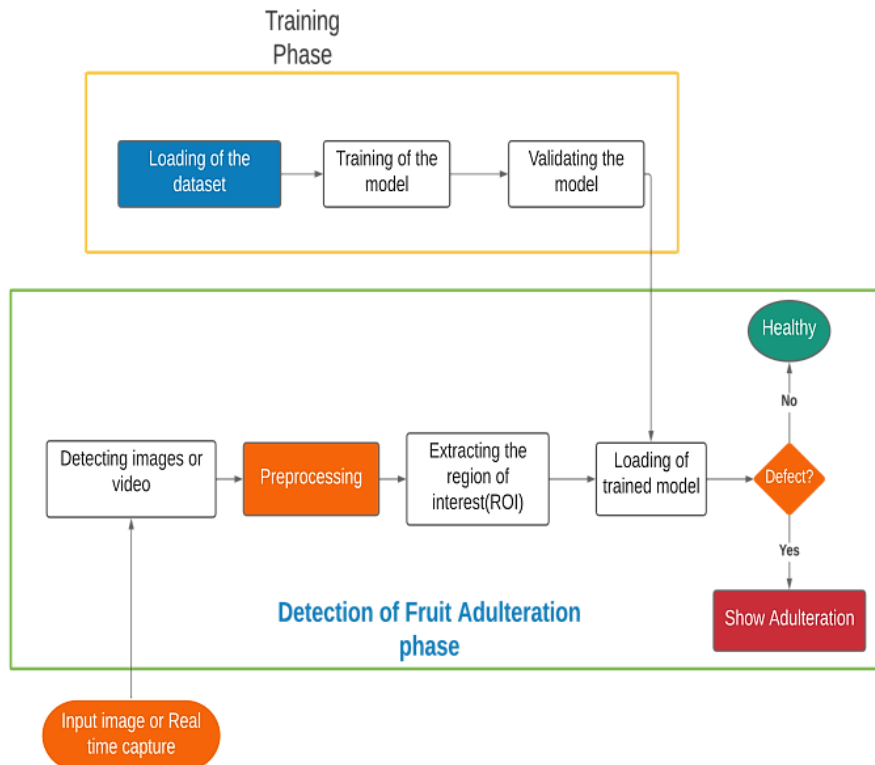

Figure 14. System architecture.

RESULTS AND DISCUSSION

The above images Figures 15 and 16 are the outcome of the hardware setup that detects formalin in fruits. It consists of Arduino Uno, a volatile gas sensor, an h-bridge, a led display conveyor belt, and DC motors.

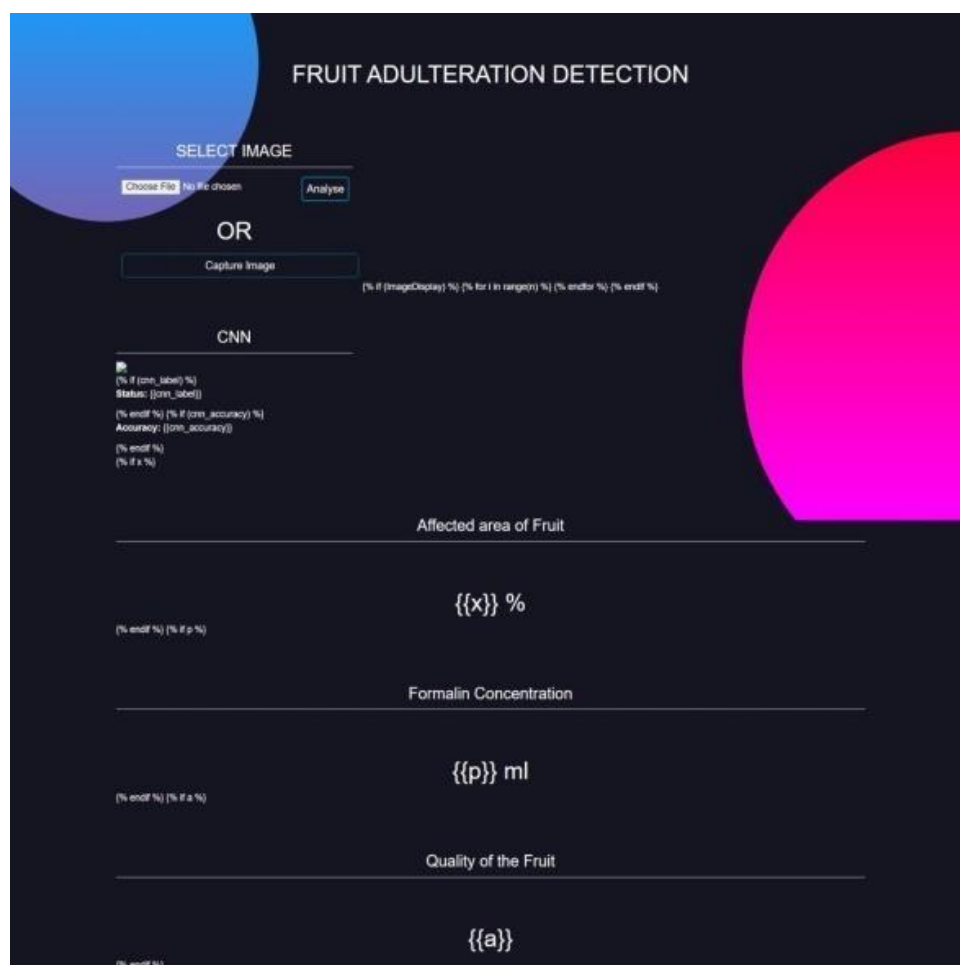**Figure 15.** Hardware Setup for Formalin Detection.

Figure 16. Fruit Adulteration Detection Page.

The above image depicts the outcome of the software page where users can upload the image and get the classified output of whether the fruit is adulterated.

Test Case 1 Test Case#	
Test Case Name	Detection of formalin below 20 PPM
Description	Reading the formalin concentration in PPM that is naturally present in fruit
Expected Output	1–19 PPM displaying on LCD
Actual Output	3 PPM (Unadulterated)
Remarks	PASS

Test Case#	#3
Test Case Name	Detection of Good Fruit
Description	Detecting and classifying good fruit using Image processing by Real-time capture or input images
Expected Output	Identification of good fruit and resulting in the forward movement of the conveyor belt
Actual Output	Because of lighting slight variation in the result
Remarks	PASS

CONCLUSION

As a result, the paper shows formalin identification using machine learning techniques. The manual approach is unable to precisely measure the formaldehyde level. The suggested system contributes to process acceleration, accuracy improvement, time reduction, and efficiency enhancement. Using OpenCV/Python, we can distinguish between fruit that is natural and fruit that is tampered with. Any fruit can be used to determine the quality using image processing. Fruit is inspected using a computer vision system instead of by hand, which delivers more accurate, equitable, and non-destructible results.

Automatic systems using vision are considered for grading and sorting fruits according to their color and size, respectively. The system is affected by changes in the conveyor's speed and lighting and camera decisions.

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