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IOT Based Monitoring Model to Identify and Classify the Grading of Fruits and Vegetables

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Abstract: - Thirty to forty percent of the fruits and vegetables harvested are discarded at this time due to the large number of employees with no training. A growing problem throughout reaping is fruit and vegetable waste because human judgment is subjective when it comes to crop recognition, categorization, and assessment. The fruit and vegetable business is in serious require of the launch and deployment of a robotic system in order to classify and grade fruits and vegetables based on their level of ripeness. Machine learning techniques can produce a sophisticated machine learning framework that can differentiate among fruits and vegetables based upon their category, variation, development, and preservation using relevant and suitable computational imaging ideas. We analyzed, contrasted, and proposed an Internet of Things-based monitoring approach in this work for identifying, classifying, and grading fruits and vegetables.

Keywords: IoT, Machine Learning, Naïve Bayes Classifier.

I. INTRODUCTION

As nutrition is an essential form of power for any living thing, hygiene and quality of food have continually been in considerable demand across the lifespan of humanity. The nutritional value of foods must be preserved since numerous external conditions, such as humidity, temperatures, and despair, may lead food to break down and rot. Food sellers therefore require oversight devices. Modern inspection systems keep an eye on pollutants that hasten or cause decay in food. Fruit and vegetable consumption poisoning can occur throughout the course of production, in along with incorrect consumption caused by unsuitable environmental conditions throughout nourishment shipment and storage. Therefore, the system of surveillance must be equipped to identify variations in temperature and humidity while transportation and storage, in alongside the presence of disagreeable fruit odors and problems with insects [20]. These days, the internet of things (IoT) and machine learning (ML) are widely used in a variety of industries. It is also widely used for tracking the nutritional value of food and accurate variable forecasting. This project builds an instrument set to assess food quality throughout transportation as well as following retention. It is made up of an imaging module and a number of diverse detectors for various applications. Fruit inspection can now be done remotely thanks to connected devices. Methods involving machine learning are used to forecast and classify the nutritional value of fruits. Additionally, we created a communication platform that alerts consumers in case of a critical situation. The following is the order of the other sections of the paper: Section II discusses the rationale for this project as well as the analysis of the issue. Section III provides a detailed overview of the method's functionality alongside the latest updates.

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II. Background

Image categorization has encountered a surge in operations in the past few years. Earlier methods used low-level and middle-level features including hue patterns, edging features, and material attributes to discriminate across broad categories of images. Heidemann (2004) has presented an unsupervised learning method that creates on its own graphic groupings using colors, histograms, and form descriptors. Let's begin by reviewing a few of the previous studies on recognizing things and visual categorization, such as: The goal of Anna et al.'s [1] work was to reduce fruit and vegetable waste by digitally distinguishing between fruits and vegetables. Paswan and Yadav [2] tackled the issue of fruit and vegetable waste by developing a solution that requires less trained sets. Furthermore, determined by the total and variation of the brightness measurements of the surrounding pixels in a picture, a powerful improved summation and disparity logarithmic (ISADH) pattern has been provided. Utilizing a single strategy which needs fewer training sessions and is more suitable for specific scenarios, Rocha et al. [3] proposed an alternative to the inexperienced examine where every attribute are basically joined and offered separately to each categorization method. Furthermore, the approach provided can be enhanced in the future by including more classes to be discriminated and by refining.

III. Methodologies

A. *The Suggested Monitoring Model*

The Fruit Integrity Assessment System is an arrangement that makes use of machinery intelligence and the global Internet of Things.

B. *Ideas and Design of Food Quality Monitoring*

A detailed architectural description is shown in Fig. 3.1. Three sections can be used to roughly divide the proposed system.

- Module for the Internet of Things: An incorporated Raspberry Pi 3B+ processor powers the machine. The firmware for the lens and machine learning techniques is stored on a class 10 flash drive that is placed into the Raspberry Pi.

The Spreadsheet database contains the predicted spectrum of characteristic limit values for humidity, temperature, propane, and PIR. PIR detectors [10], DHT11 [8], and MQ5 [9] are used for assessing fruit attributes [1][2], which are subsequently fed by machine learning (ML) algorithms involving Support Vector Machine, or SVM, and Random Forest [4].

- Machine learning module: Three machine learning techniques are used. An SVM, or random forest detector, is used to forecast sensor data. Convolutional Neural Networks (CNN) are used to forecast pictures [3].

- The alert module tells the user whether the fruit is edible or not. An warning will be given for each photo and sensor characteristic. The GSM module allows the image and sensor output to be sent to the user's mobile device via text message. Use the DHT 11 sensor [8] to measure differences in temperature and humidity. Both the temperature and the humidity are represented in degrees Celsius (°C) and proportions (%), respectively.

Additionally, we employ PIR [10] and MQ5[9] detectors, correspondingly, to find any type of active creature, including pests, and to identify the fermentation of propane gas. The results of PIR and MQ5 are either 0 or 1. The amount that the detectors have identified will be sent to the computations. Subsequently, the simulated dataset's minimum value is contrasted using the target input group's quantity. Positive numbers fall exterior of the criterion spectrum, and unacceptable ones fall inside it. After that, a text notification will be sent to the consumer's mobile. If the instrument notices changes in moisture or temperature readings, projections are made using the Random Forest approach. This alert is generated as a communication. The MQ5 detector not only reports a value of 1, but it also notifies users that "gas is found." If it's not present, the value is 0. If the PIR sensor detects any, an alert notification indicating "bugs is identified" will be displayed, and the value will be 1. If it's not present, the value is 0. The fruit is then photographed using a webcam. The graphic will next be fed into a deep learning technique called Convolutional Neural Network, or CNN. CNN determines how much a graphic is excellent or bad through contrasting it to the initial record. It further provides you a number that shows how likely it is that the fruit will be nice or horrible. Furthermore, an alarm will be sent to the user. The forecasts indicate that maybe the fruit is in their natural state. The user receives a notification about the fruit's condition via the GSM module that is installed.

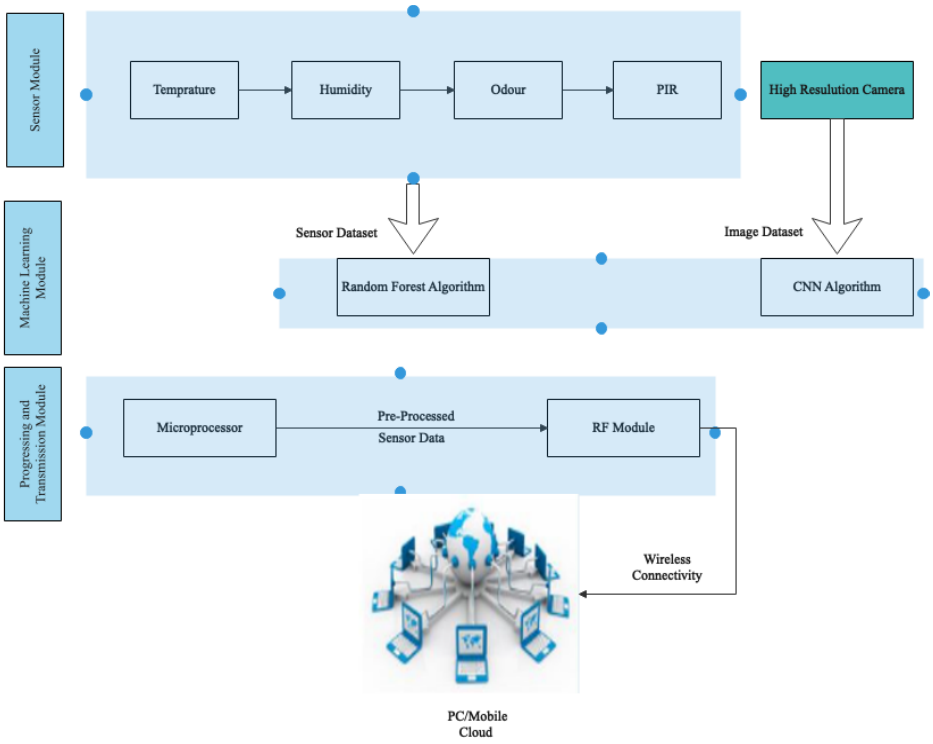

Fig 3.1. Block Diagram for Grading of Fruits and Vegetable Monitoring Model

C. *Implementation*

An overview of the system in place is given in Figure 3.2. Along with combining and customization of the necessary gadget modules, the main software implementation was completed.

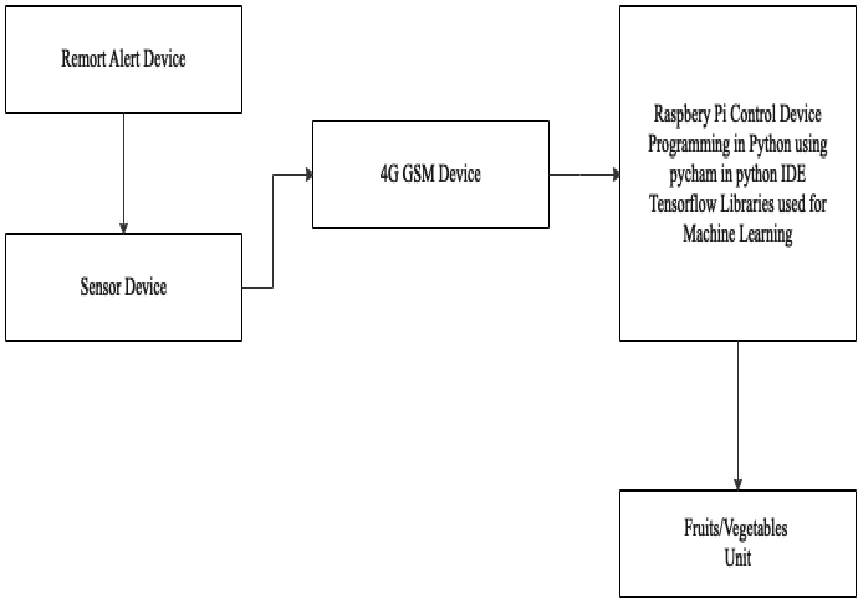

Fig. 3.2. Working Mechanism for Fruits/Vegetables Grading Monitoring Model

Measuring Freshness: Fruits change in temperature and humidity to maintain crispness. Furthermore, as the fruits decay, germs might be current, giving off a horrible stench. Fruit that goes bad and releases an odor is usually caused by the growth of yeast, bacterium, and mold, which are rotting microorganisms. Odors can originate from two sources: either the bacteria directly produce the smells, or they release the smells when they break down the food. Fruits release a substance called which causes a quick and spectacular maturation procedure that can increase the odor. [21]. Utilizing the readings of the DHT11[8] detector and measurements of the temperature (in °C) and humidity (in %), the freshness of the fruit is assessed. Fruit with a Celsius output between 0°C and 35°C is deemed to be very fresh. Despite the fact that it's under cooling, the fruit is still edible. Anything above 35 °C is too heated to eat fruit. If the humidity output is between 45% and 70%, the fruit is very fresh. If the amount used is greater than 70% or less than 45%, the fruit should not be consumed. If the output of the MQ5 gas sensor [9] is 1, then gas is present. However, if the value is zero, there is no gas at all. A PIR [10] sensor's output of 1 indicates the presence of pests. If, however, the value is zero, then the pest does not exist. building of the dataset (The five columns in the excel table we create as a dataset for the sensor findings are temperature, humidity, methane, PIR, and status). In the event that all sensor outputs fall within the threshold value, status is 1. If any sensor value deviates from the threshold, the status is set to 0. Using a camera and a smartphone, photos are taken for the training and testing datasets in the process of collecting image datasets [6][7]. There are 13,599 images of fruits [13], including bananas, oranges, and apples. Fruits with varied degrees of disease are shown in the photographs alongside healthy, disease-free fruits; the former are regarded as normal fruits. fruit that is classified as low, medium, or high in the three stages. Fruits with low levels of infection have few dots on their surface. The medium-level diseased fruits have more, darker marks. The high-level sick fruits have changed color and have a fractured surface [21].

D. Machine Learning and Deep Learning Algorithms for Monitoring Models

The random forest is a supervised learning technique that has two applications: classification and regression. Since trees form a forest's base, a forest with a larger tree count will be stronger. Hence, the random forest technique creates decision trees from data samples, gets forecasts from each one, and then utilizes voting to decide which is preferable. This ensemble technique minimizes over-fitting and is therefore better than a single decision tree because it averages the findings. To illustrate how the Random Forest algorithm works, the subsequent steps are summed up in Fig. 3.3.

a) Choose random samples first from a pre-existing dataset.

b) For each sample, this algorithm will build a decision tree. The forecast outcome from each decision tree will then be obtained.

c) Every anticipated outcome will be put to a vote.

d) Choose the predicted result that received the most votes to be the final outcome [18].

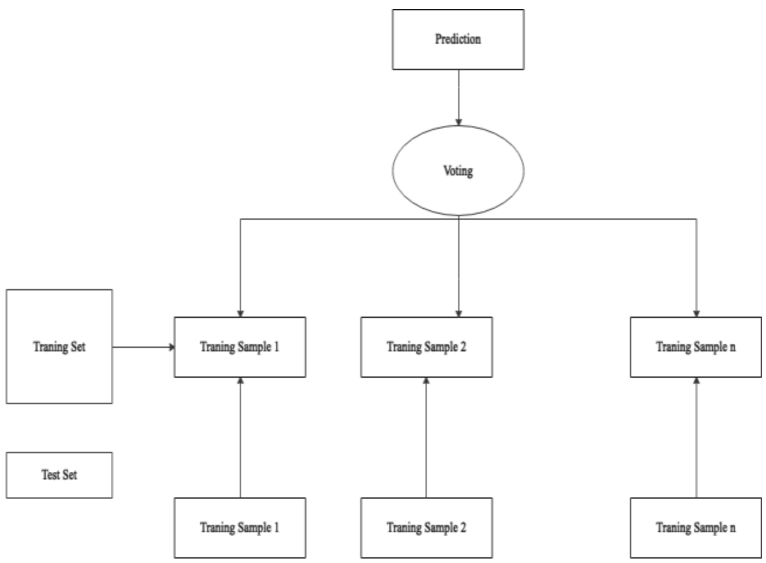

Fig. 3.3. Working Mechanism of Random Forest Algorithm [18]

E. Support Vector Machine

The goal of the support vector machine approach is to find a hyperplane in an N-dimensional space (where N is the number of features) that categorically classifies the data. To split the two sets of data points, there are a lot of different hyperplanes to pick from. Finding a plane with the maximum margin, or the maximum distance between the data points of the two classes, is the aim. It is useful to optimize the margin distance (see Fig. 3) so that subsequent data points can be classified with more confidence. See [14] for references.

F. Convolutional Nural Network

The study of visual imagery is the most popular use of convolutional neural networks in deep learning. The layers in CNNs are ordered according to three dimensions: width, height, and depth. Additionally, not all of the neurons in the layer above it are connected to even a small percentage of the neurons in the layer below. The ultimate reduction of the final output will be a single vector of probability scores ordered along the depth dimension [19]. CNN is divided into two main categories:

A sequence of convolutions and pooling operations are carried out by the network in the feature extraction phase to detect the features.

b) Classification: In this case, these retrieved features will be layered upon by fully connected layers, which act as a classifier. According on the algorithm's prediction, they will assign a probability to the object on the image [23].

The machine learning unit gets the outputs from the cameras and sensors as a test dataset. We have utilized a machine learning algorithm to determine if the fruit is ripe, rotting, or uncooked. By comparing the training and test datasets, the algorithm generates predictions. The predictions could be fresh or defective fruits. If it is destroyed, the vendor will be notified using a mobile application.

By using the following categories of measurements and analysis, we have examined the accuracy of our implementation:.

c) Measurement of Sensor values under various atmospheric conditions

To investigate the precision of sensor readings, we have conducted measurements in a range of air conditions. If the DHT11 sensor's temperature output falls between 0°C and 35°C, the fruit is exceptionally fresh. When the temperature drops below freezing or rises beyond 35°C, fruit should not be consumed. If the DHT11 sensor's humidity output is between 45% and 70%, the fruit is exceptionally fresh. If the percentage is less than 45% or higher than 70%, the fruit shouldn't be consumed. If the gas sensor's output (from the MQ5 sensor) is 1, then gas is present. If the value is zero, then there is no gas present. The presence of pests is indicated when the PIR sensor returns a value of 1. However, if the value is zero, the pest is not there. Whether the fruit is fresh or decaying depends on the outcome of these four factors. The results shown in Table I provide evidence of the correctness of the system.

Table I. sensor value measurements

Atmospstererich Conditions	**Measure Value**			
	Temperature	**Humidity**	**Odor**	**Pest**
Below normal condition	26	55	1	1
Close to heating	130	25	0	0
About to fridge	-16	100	0	0

d) Analysis of Precision of ML Algorithm

We performed a behavior study of our machine learning system and discovered that it operated consistently by taking into account different prediction scenarios, as shown in Table IV.

Table II. machine learning algorithm precision analysis

Quality Prediction Condition	Machine Learning Algorithm Behavior Analysis		
	Detected	Not Detected	Partially Detected
Below normal condition	Yes	-	-
Close to heating	-	-	Yes
About to fridge	-	-	Yes

e) Analysis of IoT Communication accuracy

We analyzed our system's Internet of Things communication while taking into account a number of variables that can affect the quality of communication, as shown in Table V. The outcomes showed that the performance was reliable. In terms of range, the GSM RF module we used worked nicely. However, because of its high energy consumption, wireless technologies such as LPWAN will have to be embraced in the future in order to provide a more efficient alternative.

TABLE III. COMMUNICATION BEHAVIOUR ANALYSIS

IoT Communion Alert Condition	**Communication Behavior Analysis**		
	Successful	**Unsuccessful**	**Remarks**
Below normal condition	Yes	-	-
Moving around withVehicle	Yes	-	-
By Installingthe Moduleinside the fridge	Yes	-	-

IV. MAJOR FINDINGS

We recommended a fruit quality monitoring system in this study to predict the freshness of fruits. By evaluating the freshness of the fruit, the user may make a more informed choice about whether or not to consume it. This method will reduce the amount of rotting fruit, which will reduce the demand for human work and income loss. Additionally, gaining the clients' trust is facilitated. This method only works when the camera is used to identify changes in the fruit from the outside. Three key goals that can be achieved by the IoT-based online monitoring strategy utilizing smart sensors are tracking fruit infection, reducing fruit waste, and improving transportation efficiency. In the event that any diseases are discovered in the fruits by machine learning surveillance before to, during, and following storage, the CNN and Random Forest classifier will identify the fruits as errors. Based on the output of the CNN and Random Forest algorithms, the system divides fruit into two categories: contaminated and healthy. The alert message is received by both the vehicle's owner and operator.

Fruit defects inside would be simple to find if spectroscopic could be altered in the future. Spectroscopy is the study of the interaction of electromagnetic radiation with matter [12]. Further LPWAN technologies and IoT services will also be incorporated in order to optimize various components and increase the overall efficiency of the system.

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