IJBPAS, December, Special Issue, 2021, 10(12): 232-243
ISSN: 2277–4998

International Journal of Biology, Pharmacy and Allied Sciences (IJBPAS)
'A Bridge Between Laboratory and Reader'
www.ijbpas.com

SENSOR BASED RIPENESS FRUIT MONITORING SYSTEM USING IMAGE PROCESSING

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Received 19th Aug. 2021; Revised 20th Sept. 2021; Accepted 29th Oct. 2021; Available online 1st Dec. 2021

https://doi.org/10.31032/IJBPAS/2021/10.12.2024

ABSTRACT

In order to offer an accurate image of the fruit's quality, quantity, and maturity, fruit monitoring is an essential tool. Observing each individual tree in a huge farm to learn about the fruits is challenging. There are various limitations to using the manual inspection technique. There are different applications of the image processing and IoT sensors in various sectors. Using image processing for crop diagnostics is popular in the agriculture business. The IoT-based system is able to remotely monitor field conditions owing to sensors. This paper presents a framework for ripe fruit monitoring using image processing and the sensor based Internet of Things (IoT). On the other hand, the correlation coefficients (R2) for fruit counting and size estimation are 0.996% and 0.998% respectively.

Keywords: Fruit monitoring, Image Processing, Ripeness, IoT

INTRODUCTION

Horticulture in the modern era employs advanced technologies for yield estimation and plant health monitoring. New techniques have been developed to improve the quality and production of crops. As technology advances, people's lifestyles change swiftly. Farming time may be reduced by new technology, allowing farmers to focus on other elements of their company [1, 2]. The farmer may monitor the health of the fruit and the surrounding environment using cameras and sensors. Solar-powered, Wi-Fi-enabled cameras are used to monitor, prevent, and manage the farm remotely. Farmers can gather data on rain, temperature, and moisture using sensors [3, 4]. Rather of using conventional methods, a farmer may monitor the entire crop growing process using IoT devices. Agriculture that is intelligent and precise makes use of image processing and the Internet of Things [5].

Smart farming leverages the Internet of Things to boost agricultural productivity, which is the backbone of the global economy. Quality and quantity of production are crucial in agriculture. Intelligent farmers may use IoT technology to determine the quantity and maturity of fruit. The farmer will arrange his harvest according to the maturity of the fruit and establish a harvest date appropriately. Farmers may begin the process of exporting or storing the fruit once it is grown. Agriculture makes extensive use of the Internet of Things (IoT) [6 – 10]. Agriculture may be able to leverage image processing to accelerate the adoption of technological solutions. The farm's whole plant collection is digitally collected and processed. To isolate the fruits from the plant's foliar region, image segmentation techniques will be used to remove the plant's foliar area from the images. Machine learning will be utilized to determine the fruit's ripeness. For instance, the Internet of Things enables huge farms to monitor their on-tree crops autonomously (IoT). This technique enables farmers to monitor their land without personally visiting it.

Smart Farming Application using Image Processing

In agriculture, image processing is used to grade, count, and harvest fruits. By addressing plant health monitoring systems, diseases, weeds, and insects may be identified. Because machine vision automates manual labor, it is frequently employed in precision agriculture. On the other hand, automated procedures are speedier but more error-prone. Additionally, machine learning in agriculture is capable of rapidly and accurately analyzing massive amounts of data. Due to technical improvements, the application of machine vision in agriculture has expanded dramatically [11 - 17]. Numerous studies have been conducted on image processing-based smart farming. In addition to agriculture, image processing may be used in medical imaging [18-20]. For apple fruit growth forecasts, Stajnko *et al*. suggested an image analysis model based on color, shape, and texture. This model counts and diameters apples, providing objective apple development modeling and yield forecasts. Color, shape, and texture of fruits were captured. A fruit identification algorithm scans 15 to 42 apple fruits on-tree effectively and detects one to three apple fruits that were overlooked or misclassified per tree. Following July, the orchard data closely matched (R2 = 0.96), allowing for reliable prediction of the predicted production per tree beginning in June. Monitoring plant development is critical in high-demand locations.

Jhuria *et al*. [22] created an image processing system that allows for the tracking of fruit infection from planting to harvesting. To train and alter the database, back propagation and artificial neural networks (ANN) are utilized. The morphology of the feature vectors in this case provides 90% accuracy. To protect crops from disease, modern agricultural technology is essential. Farmers can use a web-based application devised by Bhange and Hingoliwala to submit photographs of ill fruit [23]. The training and testing datasets are constructed using images of pomegranate fruits.

To determine the severity of a condition, the user's photographs are compared to images from the training dataset. Before extracting attributes, the image must be scaled. The second stage is to determine if a picture is unwell using k-means clustering and subsequently an SVM classifier. At 82 percent, the morphological characteristic is the most accurate of the three retrieved attributes. Dorj *et al*. devised a novel algorithm for citrus fruit counting [24]. This method compares data from orange orchards to human counting in natural light. The yield of citrus on-tree was analyzed and compared using image processing and other approaches. RGB to HSV conversion, thresholding, orange color detection, and noise reduction are all recommended techniques. In citrus fruits, the distance transform and marker-controlled automatic watershed segmentation performed effectively. For estimating the yield of one citrus tree, the counting algorithm and human observation have an R2 of 0.93. Bargoti and Underwood [25] provide an R-CNN-based fruit recognition system that utilizes three orchard fruit inputs: apples, mangos, and almonds. Few prior pictures, tactics like as flipping and scaling growths have been shown to boost results. It was used to count fruit in orchards, a process that necessitated a large number of photos.

Hassan and Nashat devised a method for identifying and classifying olive fruits [26]. Utilizing texture analysis and a texture homogeneity measure. The Canny, Otsu, K-means, and Fuzzy C-Means algorithms were studied in this work. The results indicate that this method outperforms every other approach evaluated. A low-cost hardware kit might be constructed using this technique. Tu *et al*. [27] proposed that avocado tree crop crown height, extent, PPC, and condition be assessed utilizing a UAS platform. This article discussed how to conduct image analysis on individual tree tops.

The Elman neural network is fed by six color and ten form attributes. The capture and counting of hidden neurons is optimized using a genetic algorithm. The absence of branches or leaves on apples can be utilized to train neural networks for increased accuracy. We compared the Elman neural network and two additional methods for recognizing occluded fruit to back-propagation techniques. This model has a 94.88 percent recognition rate and a 100 percent training success rate. The identification rates for overlapping and hidden fruit were 88.67 and 93.64 percent correct, respectively.

Smart Farming Application using IoT

New science and technology are bringing the Internet of Things to rural areas (IoT). ICT-based ranch management is a new concept that leverages existing information technology to increase product quantity and quality while reducing labor needs. Sensors, robots, software, and data analytics allow IoT-connected smart farming. Many research have been done on IoT-enabled smart agriculture. Numerous studies on IoT-enabled smart farming exist.

Ram Kumar and others engage in a debate over the use of drones in agriculture [28]. Drones may be programmed to detect soil moisture in order to monitor livestock and logistics. According to a comprehensive study, integrating rambles transforms traditional farming into Smart Farming. Drones can be launched in remote areas, reprogrammed and customized to the project's specifications, and can measure anything. Hossain *et al*. [29] developed a 5G image categorization system.

Deep learning is used to fine-tune pre-trained models in the suggested technique. Through the use of edge computing and caching, images are sent in real time. Hossain and Muhammad proposed a privacy-preserving automated emotion recognition system based on edge clouds [30]. This solution utilized the Internet of Things (IoT) devices of the user to gather face and voice signals.

Pre-processed signals are sent from outlying clouds to the core cloud. The purpose of this project is to extract deep-learning properties from pictures and audio using a CNN-based pre-train model. Following that, the input is classified using a support vector machine. For the RML database, the proposed approach was 82.3 percent accurate, while for eNTERFACE'05, it was 86.6 percent accurate. Jha *et al*. [31] investigated automated processes such as the Internet of Things, wireless communications, machine learning, artificial intelligence, and deep learning [32-36].

PROPOSED METHOD

The primary objective is to bridge the divide between image processing and IoT principles. The camera, IoT gateway for the phone, and image processing system are the system's primary components. The farmer inquires as to the processor's current employment status. The camera photos the farm on demand from the processor.

The processor extracts the picture and then analyses it to provide information about the captured fruits' present state. The processor then sends a text message to the farm informing them of the fruit's status. For a real-time application, the best and most convenient solution is an IP camera, a Raspberry CPU, and a smartphone. **Figure 1** depicts a detailed schematic of the manufacturing process.

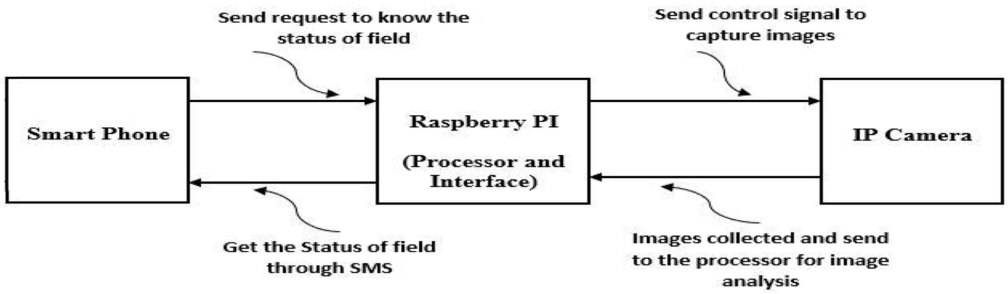

Figure 1: Schematic of the manufacturing process

CAMERA

Network cameras, in contrast to webcams and traditional analog CCTV cameras, are networked. USB and coax connections are available for web and analog CCTV cameras. Network cameras, on the other hand, may be easily accessed over a network. Every network camera has a CPU and memory. IP cameras (Internet protocol cameras) must be configured in such a way that they identify themselves as having a direct Internet connection for data transmission and reception. Once configured, an IP camera may be seen remotely through a network-connected mobile device (phone, PC, or tablet). The router or NVR uses this address to send data to the IP camera.

As a result, the user must locate the appropriate IP camera address online. The Dynamic Host Configuration Protocol determines the IP address of a computer (DHCP).

RASPBERRY PI BOARD

In real-time applications, the Raspberry Pi is utilized to simplify the system through the usage of MATLAB, a single-board computer. Raspberry Pi is used to monitor fruit using picture processing. We use image processing to count fruits and estimate their size relative to the canopy.

SMART PHONE

Smartphones have become more prevalent in recent years. Internet access is facilitated by the smartphone. In this scenario, we're providing the IP address of the smartphone to allow the Raspberry PI to connect. To do this, change the IP address of the computer from DHCP to static and enter the needed address.

COUNT AND SIZE MEASUREMENT FRUITS

Color recognition is the primary process by which the human visual system distinguishes between green and red mango fruits. Three factors make image processing distinctive. Separation of color spaces eliminates the backdrop. Second, the mango's kilograms weight. Using canopy images, count and estimate the size of on-tree fruits in **Figure 2**. It must first be processed to determine the origin of the items, and then validated to determine if the initial objects are fruit. These techniques separate the fruit from its environment (which includes the sky, trees, branches, the ground, and other types of noise). Withdrawal can be mild, moderate, or severe, depending on the context. The background in this image has been removed using a color thresholding and morphological approach. After that, the ellipse is fitted with RHT. The ellipse is shaped by the fruit's outliers/arcs. The RHT can identify fruits if an ellipse can be fitted around their edges. This is only feasible if the image is partially or completely obscured.

These procedures can be used to estimate the yield of a tree.

- To begin, we capture a shot in reasonable light with a standard RGB camera.
- By changing color components in photos, the Color Threshold application assists in thresholding color images in a variety of color spaces. This eliminates the background.
- We employ morphological techniques to eliminate the tiniest components. Strel is used to construct structures.
- The Hough Transform is commonly used in image analysis to evaluate lines and curves. As a result, some curves, such as an ellipse, are rendered invisible. The Randomized Hough Transform is used to locate ellipses.
- The label block may be used to indicate anything about the backdrop. White on a black background, the item is white. The first pixel of an item is 1, the second is 2, and so on. Giving each object a unique name is an excellent idea. Additionally, it keeps track of the quantity of fruits on the tree.
- Separate it from the others to ascertain its size. The width and height of a pixel are included in its area. Then we can determine the height and breadth of each object. Apart from the principal and minor axes. The pixel value is converted to cm in this scenario.

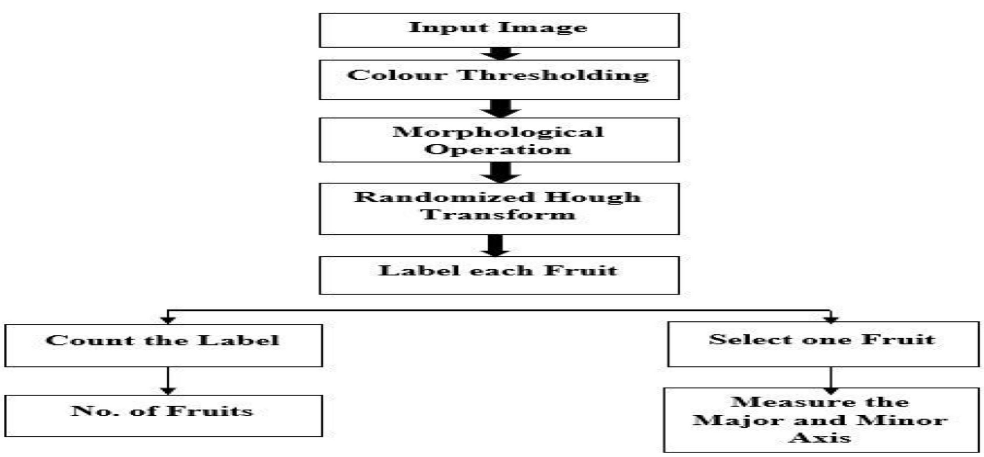

Figure 2: Count and size estimate the size of fruits

RESULT AND DISCUSSION

To eliminate the backdrop from an RGB image, color thresholding in the L*a*b color space is used. Due to the fact that the shoot is on-tree, the backdrop cannot be completely eliminated.

Smaller spots can be eliminated using the morphological binary approach. After that, we used RHT to label produce with packaging.

Fruits have the same boundary boxes as vegetables. A second citrus is chosen to determine its size. The backdrop is eliminated by a binarization and morphological method. The primary and minor axes are determined by RHT. The complete operation is depicted in **Figure 3**.

RHT determines tree fruit count and size, the solution uses a Raspberry Pi. When the phone rings, the Raspberry Pi replies by activating the PI camera. The PI camera comes equipped with its own memory. Following that, the Raspberry Pi extracts and processes the images. Following processing, a mobile device can obtain a link to the location of the tree's fruit. Numerous cameras on the farm are solar-powered. The raspberry pi camera enters standby mode in response to the raspberry pi's instructions.

To perform an experiment, we took twenty photographs of the fruit on the tree. The scatter plot in **Figure 2** depicts the manual and algorithmic counts. Again, 20 samples are chosen. The fruits may be used to determine the area. The area of a polygon is calculated by multiplying the major and minor axes. Because the main and minor axes of an ellipse fitted to a fruit are known, it is possible to forecast the fruit's area. Fruits are manually measured using slide calipers and centimeters.

To retain the connection between manual and algorithmic measurements, we raised the manual measurement of the fruit by a factor. The performance of the algorithm is seen in **Figure 5**. R2 values of 0.996 and 0.998 are shown in **Figures 4 and 5** for fruit counting and size estimation, respectively.

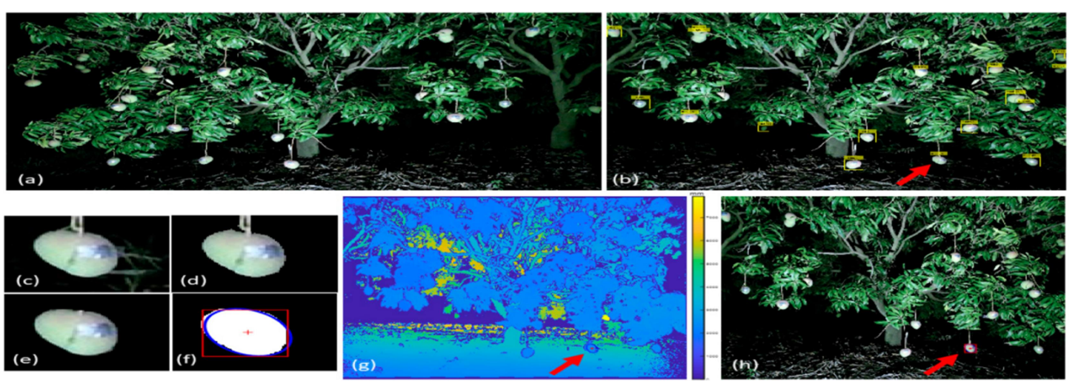

Figure 3: Various stages of Sensor Based Ripeness Fruit Monitoring System using Image Processing

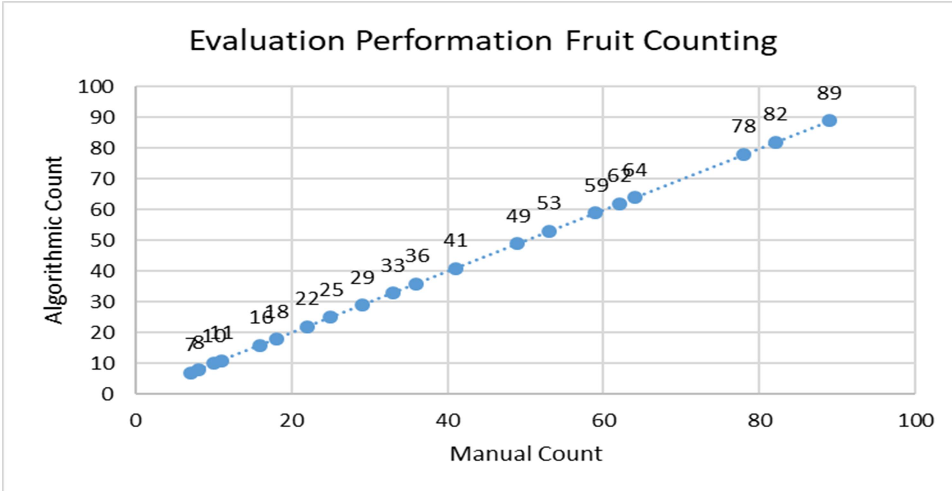

Figure 4: Evaluation Performance Fruit Counting

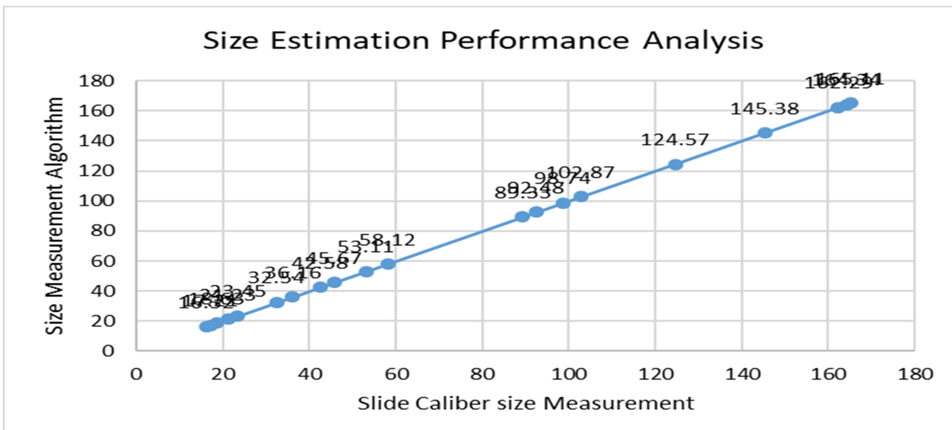

Figure 5: Size Estimation Performance Analysis

CONCLUSION

To count and estimate the size of fruits, color thresholding, morphological techniques, tagging and RHT may be used. The system is monitored using a Raspberry Pi, a PI camera, and a smartphone. Apart from monitoring fruit production, this operation is solely intended to aid the export and storage systems in supplying fresh fruit on a timely basis. Our practices will now be monitored and regulated. Additionally, robotic fruit harvesting will be used into future localization efforts. In smart farming, temperature and rain sensors will be used to monitor fruit maturity and damage. A constant or uninterruptible internet connection is required for smart farming. That is why farming in rural areas, particularly in developing nations, is challenging.

ACKNOWLEDGEMENT

The authors express their sincere gratitude to The Management, Krupanidhi Group of Institutions for supporting the research work carried out through Krupanidhi Research Incubator Centre (K-RIC) program under Krupanidhi Group of

Institutions, Krupanidhi Degree College and Krupanidhi College of Pharmacy.

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