Research Article

Intelligent fruit sorter for quality evaluation of guava fruit using image analysis

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ABSTRACT

The growing Indian population, post-harvest losses and the ever-increasing demand of high quality, export-grade products which are produced under stringent safety protocols and standards highlights the need to establish stringent, swift, and objective quality evaluation procedures to food and agricultural products. The aim of this research was to develop a smart fruit sorting machine that would distinguish healthy and flawed guavas. The device is made up of a conveyor belt, a separator, an optical sensor array, and an Arduino Uno microcontroller board. Based on image-analysis algorithms that were run on an embedded system architecture. The experiment was run on a field-programmable array which was implemented on a programmable logic controller, running machine-learning algorithms on Matlab and coordinating the functionality of the relay with the use of MATLAB. The system was experimentally tested and proved accurate by physical sorting and checking 200 samples, with an accuracy of 97% of healthy and damaged fruits being identified based on spectral differentiation in the conveyor-segregator subsystem.

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INTRODUCTION

Horticulture and agriculture are central to the emerging economy of India, and the healthiness of fruit products is one of the key factors of consumer choice. To satisfy this need, suppliers have to provide fruit of invariably high quality. Fruit processing follows a sequence of operations, which include; grading, sorting, packing, transport and storage but grading has been identified as the most important operation in terms of high quality processing. Currently, grading is done manually in India by professional human graders where they grade external qualities like size, colour intensity, shape and surface appearance in addition to internal qualities like sugar and acid content. However, external to the internal degradation is the most important measure used to grade and sort guava. This

research paper proposes a thermographic imaging-based analytical and sorting system, which is based on computer-vision and image-processing algorithms and, therefore, speeds up the assessment process and removes the aspect of human error [1].

Guava is a tropical fruit that is honored with a unique taste, smell, and health value, which requires under careful quality analysis to meet the demands of the consumers and sustain competitiveness in the market. The traditional methods of grading guava are manual, time consuming and prone to subjectivity hence inefficiencies and inconsistency. The recent progress in the field of image analysis and machine-learning has opened the possibilities of automating the process of assessing fruits [2,3]. With the combination of computer vision and artificial intelligence, intelligent sorting system can assess dimensions, hue, morphology, and surface anomalies of guavas at high speed and accuracy. In the present paper, I am going to describe a machine-learning-based image-analysis system that categorizes guava fruit in predetermined quality types [4-6]. The ensuing automation will guarantee improved efficiency in operations, less expenditure on workforce, and improved quality control in producing guava. The empirical results are of great importance to the agricultural industry among them by improving the business sustainability of guava farmers. Furthermore, the suggested system will provide the basis on the expansion of intelligent sorting to other fruits, thus, leading to development of innovative technology and sustainable agriculture practices [7,8].

Related Work

Automation techs have been bumped on the agri-industry over the years all geared towards reinforcing efficiency and reducing labor expenses. It has taken a lot of effort to design intelligent fruit sorters which rely on image analysis as a way of measuring quality. Guava (Psidium guajava) is a tropical fruit rich in nutrients and has cash-value hence is a good candidate in automated sorting systems [9-11]. There are a number of papers, which demonstrated that image analysis would be used to sort fruit. The case in point is Wang et al. (2018) created a computer-vision system that categorized apples by color and size and reached a rather high accuracy. Li et al. (2020) conducted citrus sorting by using machine-learning models targeting external defects, and they were able to achieve more than 90 per cent classification accuracy [12-14]. In the case of guava, the number of papers on automatic sorting is not high. Nevertheless, the concepts of other fruit-sorting projects are expected to be effective in guava. An example is Take Guo et al. (2019) who developed a jujube sorting system based on color, size, and shape, and demonstrated that the systems might be applicable to quality studies [15-20].

The primary problem with the guavas is that they are tricky due to their huge variations in size, shape, and color. Others are small, others are large, and then spice it up with

ripeness and blemishes on the surface. To deal with that, you require more smooth image-processing. Although there is no much research done on smart guava sorting, a glance at general fruit sorting literature will offer you some tricks on which to snatch guava. This is the reason why we chose to invest in the construction of a robust sorting system, which would be sensitive to the peculiarities of guava and would increase the efficiency and quality in the processing of guava [21-24]. What makes this study so cool is that it combines thermal imaging and ML in the process of automatically detecting spoilt guavas. This approach outmuscles frequent hand-checks in a number of ways. To begin with, you are able to perform an inspection of the inside of the fruit without its destruction (thermal imaging) something that you cannot always notice when you take a glance at the surface. Second, you can apply ML to automatically put guavas into their thermal signature and therefore you can evaluate quality fast and effectively. The paper has the potential to establish viable methods of testing the quality of fruits and can be utilized in the agribusiness to enhance the systems of sorting and grading of guavas..

SORTING MACHINE DESIGN

The essential components of a guava fruit sorting machine were put together in the form of a conveyor system, an inspection unit, a segregator and an integrated controller. In essence, all these were to have been in unison in a single unit to form an automatic sorter of fruits. The designed automatic sorting system was tested after a standard procedure using guava fruits after a test to determine whether it was effective or not [25].

a) Image Acquisition: We are basically photographing guavas in a controlled setting with a steady flow of light to maintain the shadows and reflections.

b) Preprocessing: First, they convert the images captured to grayscale to make subsequent analysis processes simpler. After that, a median filter is used to reduce noise and thus improve the visual fidelity of the image in general.

c) Segmentation: It can be used to isolate the guava fruit against the background using the thresholding algorithm proposed by Otsu since the algorithm automatically adjusts the ideal threshold value. The binary representation is then refined using subsequent morphological processes namely hole filling and removal of other tiny objects.

d) Feature Extraction: The necessary features are systematically obtained out of the segmented image. The color characteristics are extracted of the original RGB image, which makes the color information identical all over the analysis. The Gray-Level Co-occurrence Matrix (GLCM) is used to extract texture features as it offers a powerful model of measuring the spatial distribution of intensity values. The geometrical properties can be

characterized in a comprehensive manner by the shape features of area, perimeter and eccentricity that are derived out of the binary image.

e) Classification: After these extracted qualities have therefore been assembled into one feature-vector, they are then fed into an already existing machine-learning device, say a support-vector machine or a decision-tree, which is then tasked with the job of making guesses about to which of the previously defined categories the guava is to be put.

f) Post-processing: The classification result is shown in Figure 1, indicating the type of guava.

The process starts by getting the images in which high resolution cameras are used to take images of guava fruits in various orientations. In order to reduce shadows and reflections, which may undermine further analysis, the use of uniform illumination is an absolute requirement. Image fidelity is further increased by pre-processing steps like Gaussian blur-based denoising, which inhibits random pixel noise. Background removal methods such as thresholding and background subtraction are used to isolate the fruit on the ground and the normalization is used to ensure all images are of equal size and location so that the evaluation can be done with consistency. Segmentation is crucial in defining different areas of the fruit; a common method to use is the thresholding provided by Otsu to differentiate between the fruit and its surrounding, and edge analysis-provided by the Canny detector - to determine the edges of the fruit. Segmentation further narrows down results through region based approaches, e.g. watershed or region growing. After segmentation, a set of feature-extraction methods are used: color properties are obtained with the help of histograms and color moments, surface texture is measured with the help of Gray-Level Co-occurrence Matrices, Local Binary patterns, and Gabor filters, and geometrical properties such as area, perimeter, circularity, and aspect ratio are defined in terms of shape descriptors. In order to build the dataset, you need a set of labeled collection of guava images by quality (e.g. good, average, poor). This data is divided into training, validation and test sets to enable strict evaluation of models. Principal Component Analysis and Recursive Feature Elimination are feature-selection tools that find the most discriminative attributes that are relevant to quality assessment. The stage of classification uses algorithms such as Support Vector Machines, Random Forests, and K -Nearest Neighbors, and convolutional neural networks, namely ResNet, VGG and custom networks, learn hierarchical representations automatically. Training These classifiers are fitted to the training data and training methods like data augmentation (rotations, flips) are used to enhance generalization. The validation set is assessed using validation metrics such as accuracy, precision, recall, and F1 -score, cross-validation is used to confirm the robustness and hyperparameters are tuned using grid or random search. When trained, the model can be implemented in an automated sorting system, a combination of industrial cameras, real time image processing software, actuators, and conveyor belts. The robotic system thus sorts and isolates guava fruits based on predictive results, thus improving the efficiency and consistency of the sorting process [26-29].

HARDWARE ARCHITECTURE

The present research was dedicated to the creation of a fruit sorter with auto-processing on the basis of healthy and defective guava. The hardware was two in number, one being an image acquisition apparatus which included a thermal camera and the other was a segregator unit and controller circuits including a microcontroller. A multispectral or hyperspectral camera is the key instrument of gathering images of guava fruits which is applied in this system. Such sensors obtain information in different wavelengths, and, therefore, allow further analysis of the topography of the fruit and its interior quality. The Arduino Uno board is the control unit of the system and it is connected to the multispecies/hyperspectral sensor and other components in the system. It converts the control signals into sorting mechanisms and obtains the sensor data. The second unit was comprised of a robotic segregator having the required electronic circuits. The automatic sorting machine construction is being separated into the following categories.

Conveyor System with Thermal Camera

A conveyor belt is made up of two or more pulleys, and a material lays in a continuous loop which rotates over them. Either one or both of the pulleys are driven and the belt and material on the belt moved forward. Belt conveyors can be of two major industrial types, including general material handling types like those that carry boxes through a factory, and bulk material handling types like those used to carry industrial and agricultural products, including grain, coal, ores, e.g. etc. Figure 1 depicts that the conveyor system has a motor, a thermal camera with a fixed distance, and two connections with DC geared motors at inspection locations. Guava fruit is transported to the segregator area through the conveyor structure without any human contact with the inspection station. Table 1 gives the conveyor specifications.

Table 1. Conveyor specifications

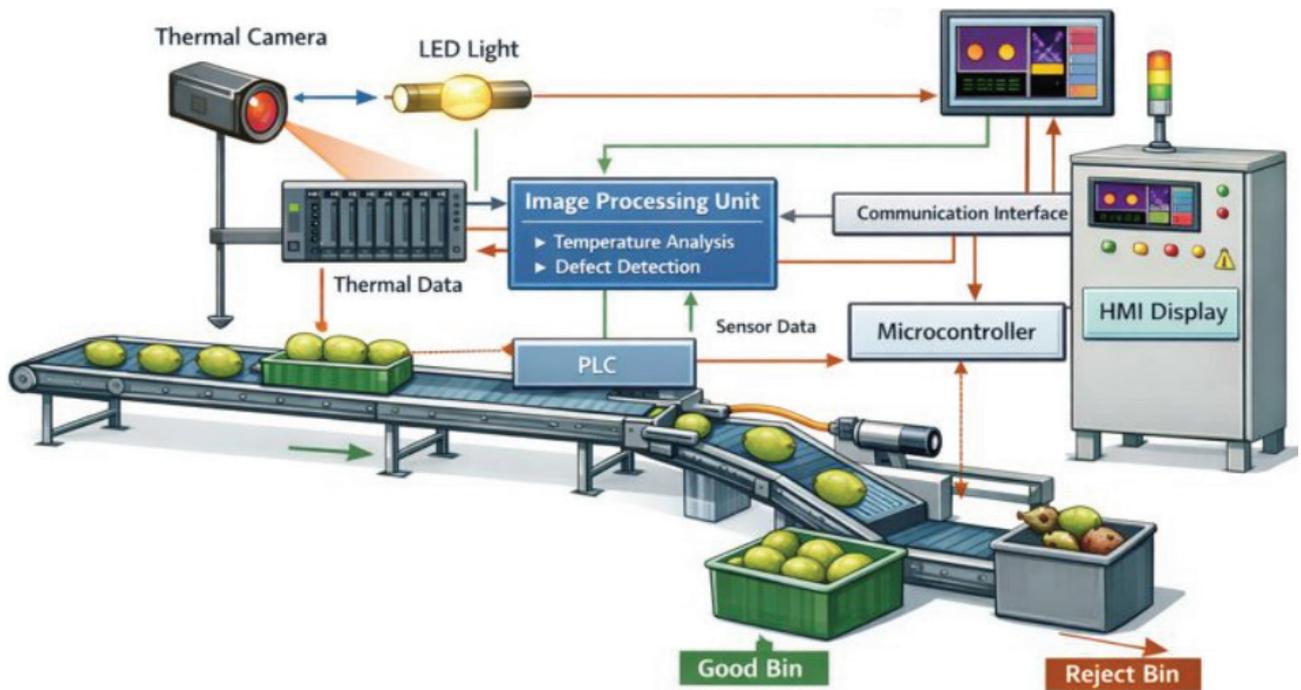| Description	Specification
Conveyor Length	2485 mm
Conveyor Breadth	990 mm
Conveyor Height	1010 mm
Conveyor /Motors Speed	90W, 230V high speed motor

Figure 1. Conveyor System with thermal camera and mechanism.

REAL-TIME GUAVA FRUIT INSPECTION WITH MATLAB INTERFACE

Guava fruit in this system is carried to the inspection station whereby it is turned by a link attached to the conveyor equipment as shown in the figure below. When the fruit reaches the point of inspection a thermal camera is used to take a picture of the fruit and the image is processed in a MATLAB interface. Figures of the surfaces of the fruit are analyzed on all sides and compared using MATLAB code and according to the results of analysis, a synchronization signal is produced and sent to a microcontroller through the MATLAB interface as in Figure 2.

Segregator as Robotic System for Separatıon of Guava Fruits

The processing of images is under consideration of health conditions, damages of birds, diseases and physical structures. The quality of the fruit is obtained by analyzing these parameters. A segregator is built and the channel configurations are made to fit the conveyor belt as in the picture given to sort out the different types of fruits. These three segregator channels are interconnected with two links and moved by a DC geared motor with an 10 rpm. The movement of the link can be controlled by the decisions relayed by the microcontroller via the matlab interface. Sound fruit enters channel 1, bad fruit goes through channel 2 and fruit with foreign content enters channel 3. This is a repetitive process in the sorting and analysis of fruit.
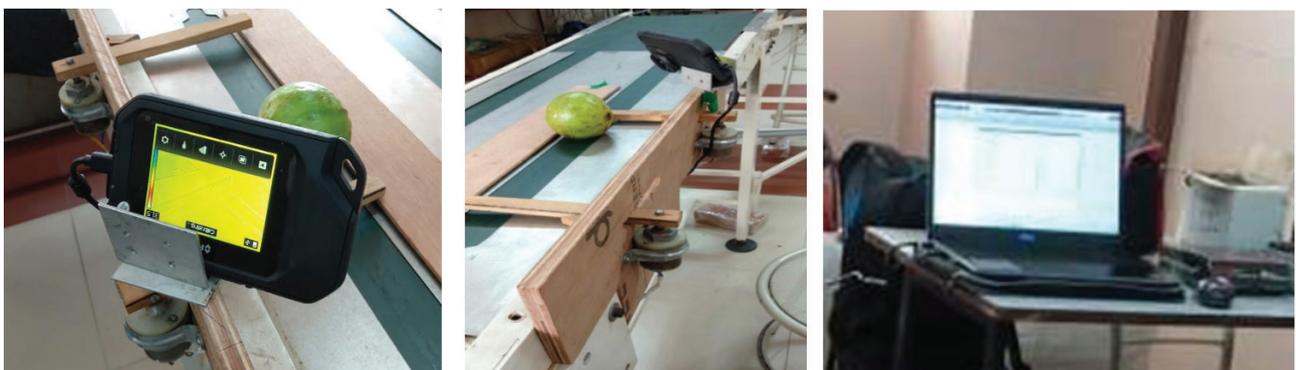

Figure 2. Realtime Inspection of guava fruit and thermal images processed in MATLAB.

Embedding of Arduıno Microcontroller and Other Auxiliary Components

The in-house system consists of an arduino microcontroller that has motor driver control, a SMPS and a 9-volt battery pack to enable automated sorting of guava fruit. The elements used in this paper include the following. Arduino 1 is connected to MATLAB which sends its signal to Arduino 2 to execute it. The conveyor motors and distributor motors will work based on the instructions issued by Arduino microcontroller and the strategic decisions passed on by Arduino 1 as shown in Figure 3. This is achieved by two L293 modules that are capable of facilitating both forward and reverse rotation of the conveyor

motors at the inspection station as well as distributor /segregator motors at the segregator as illustrated in Figure 4. The L293D module takes in signals of the microprocessor and sends the relevant signals to the motors, so as to control the conveyor link that allows the fruit inspection and separation in accordance with the MATLAB results, as shown in Figure 5. Figure 6 gives the circuit diagram of real-time inspection of guava fruit on the conveyor.

Working and Assembly of Sorting Machine

This work imagines the implementation of thermal imaging together with a MATLAB interface, a conveyor belt, and an automatic segregator to be used to ease
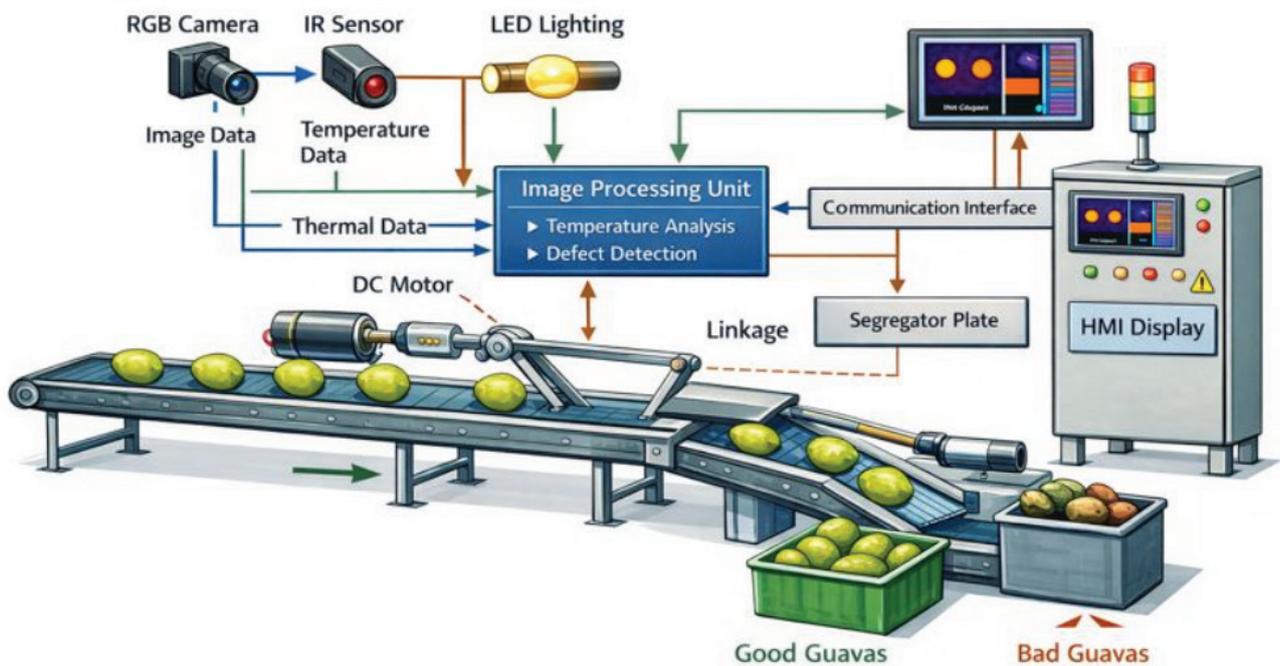

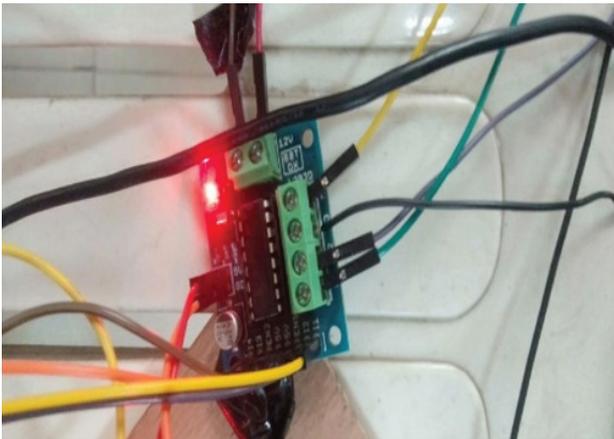**Figure 3.** Segregator system with DC motor and linkage.

Arduino 1 – MATLAB operation

Figure 4. Segregator system with DC motor and linkage.

Arduino 2 – DC Motor Operation

L293D Module – 1 – for Conveyor DC motor

L293D Module – 2 – for Segregator DC motor
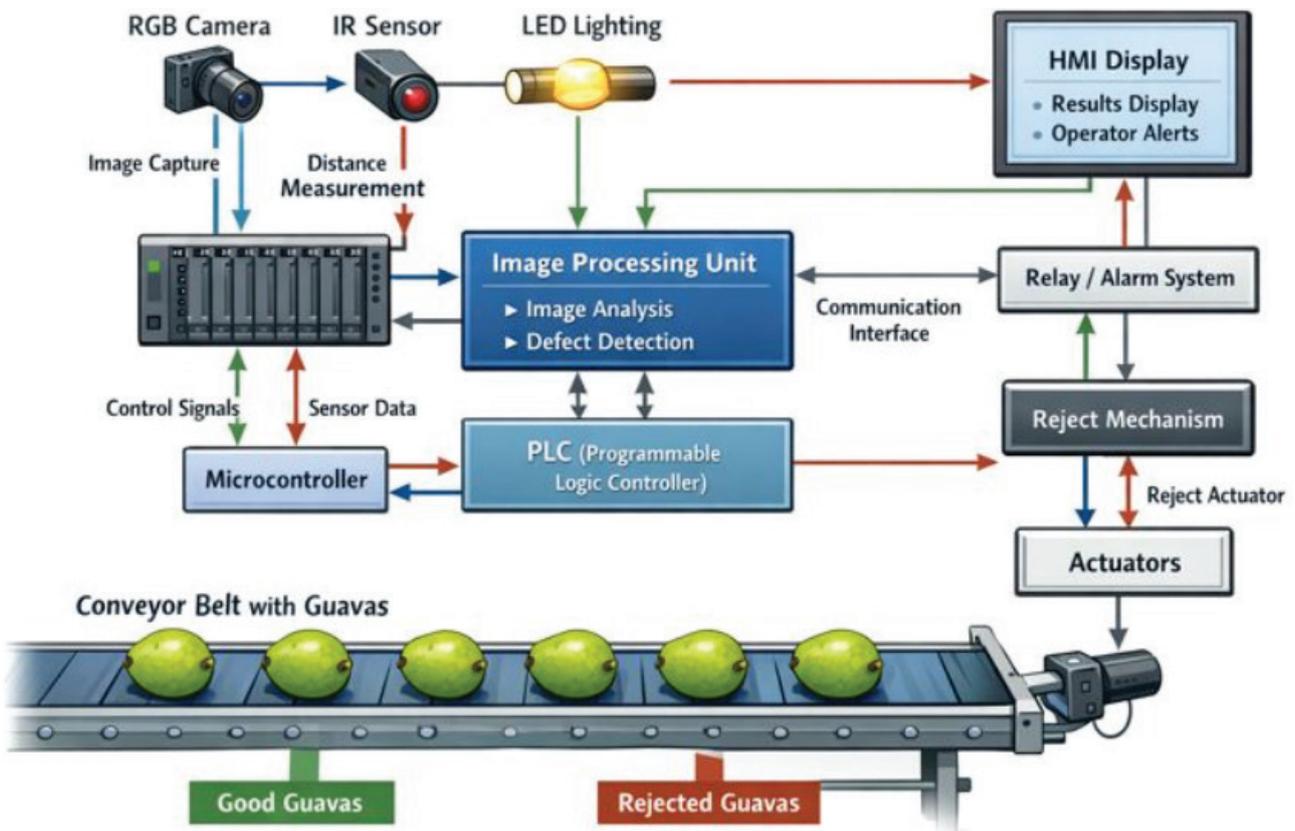
Figure 5. Module for DC motor.

Figure 6. Circuit diagram for real-time inspection of guava fruit on conveyor.

extraction of bad guava fruit in real-time in a conveyor. An Arduino microcontroller is important in aligning all the working parts as shown in Figure 7. On activation, the conveyor motor starts rotating, which controls the movement of the guava-feeding belt. A variety of fruit type is taken at one end of the belt. The fruit is then transported to the inspection center using a 2-link system which is operated by a DC motor. The program that comes with it is designed in such a way that it does not allow the next link to develop until the entire guava that is already there is inspected and no other fruit has reached. The initial connection in turn arrests the guava, which is then transferred sequentially to
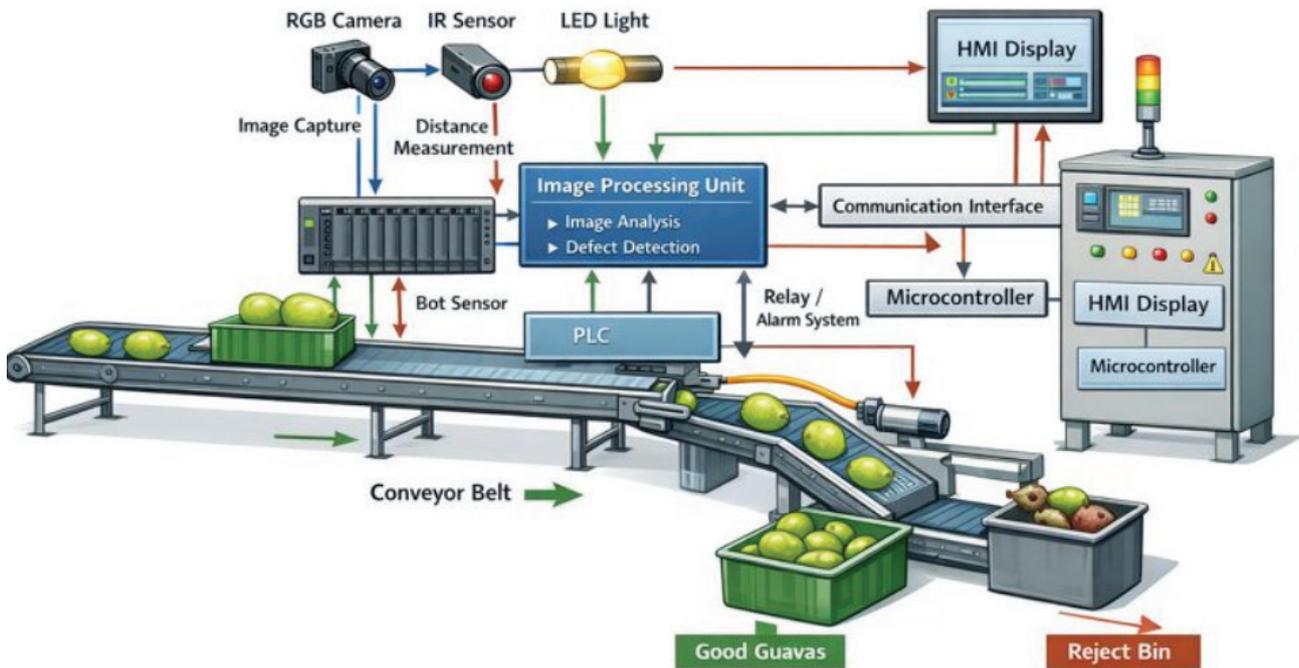
Figure 7. Schematic diagram for Guava sorting machine.

the second connection which serves as the inspection station. In the second connection, the fruit is put on a platform that is meant to process the images to measure its external quality. Thermal camera module gets the picture of the fruit and does the quality check. The embedded system then delivers a signal to the sorting mechanism which is dictated upon by embedded programming. The sorting/segregating mechanism receives the fruit through the conveyor. This is a mechanism that has a linkage that turns with the signal of the embedded module. When the fruit enters the terminal segregating unit, it drops onto the segregator because of the force of gravity. The connection initiates after getting the signal and lays the fruit in the right channel based on its quality as shown in Figure 7.

The system involves three different channels of distribution specifically designed in the segregation of guava fruits into healthy and defective ones. Two DC motors are used to activate each channel as directed by a decision signal produced by an embedded control unit. In this arrangement, processing time is significantly reduced and throughput is increased through the constant running of the analysis and sorting system. The assembled design of these components is shown in Figure 8. The core of this structure is a MATLAB interface with an Arduino microcontroller. This integrative scheme involves using the high data processing and graphic abilities of MATLAB and the direct communication capabilities of Arduino so that more complex systems can be designed with Arduino collecting sensor information, processing it and sending control instructions to actuators and MATLAB simultaneously decoding sensor information streams and sending control instructions to the Arduino.

In order to communicate with an Arduino board, it is necessary to use MATLAB Arduino support package that can support a wired (USB) and wireless connection. This package provides sensor acquisition routines, pin-level output routines and bilateral data exchange between the MATLAB and the Arduino firmware. Photographs taken by the multispectral or hyperspectral cameras are handled in this context, and spectral imaging operations are performed using MATLAB and spectral signatures are extracted and machine-learning algorithms run to label the guava fruits based on quality. The sorting scheme is a real-time PLC controlled element which is fed with classification results by Matlab. After the classification process, the quality class of each fruit was passed to the PLC. The communication protocol is often based upon common industrial protocols like Modbus, OPC (OLE for Process Control), or direct I/O connecting, based on system architecture and need. Classification data are supplied to the PLC which, using preset ladder logic or structured text, triggers relays that provide motive to the appropriate sorting devices, such as conveyor belts, robotic arms or pneumatic systems. When a fruit is considered to be high-quality, PLC activates the relay of the high-quality bin, and vice versa. Such a close coordination guarantees that sorting is both fast and accurate, which can be attributed to the fact that MATLAB is able to perform computational processing of image analytics and PLC does mechanical processing. The smart system of sorting fruits is specifically designed with a user-friendly graphical user interface that makes interaction amongst operators possible. The focus on simplicity and ease of navigation is the number one priority; the interface will contain
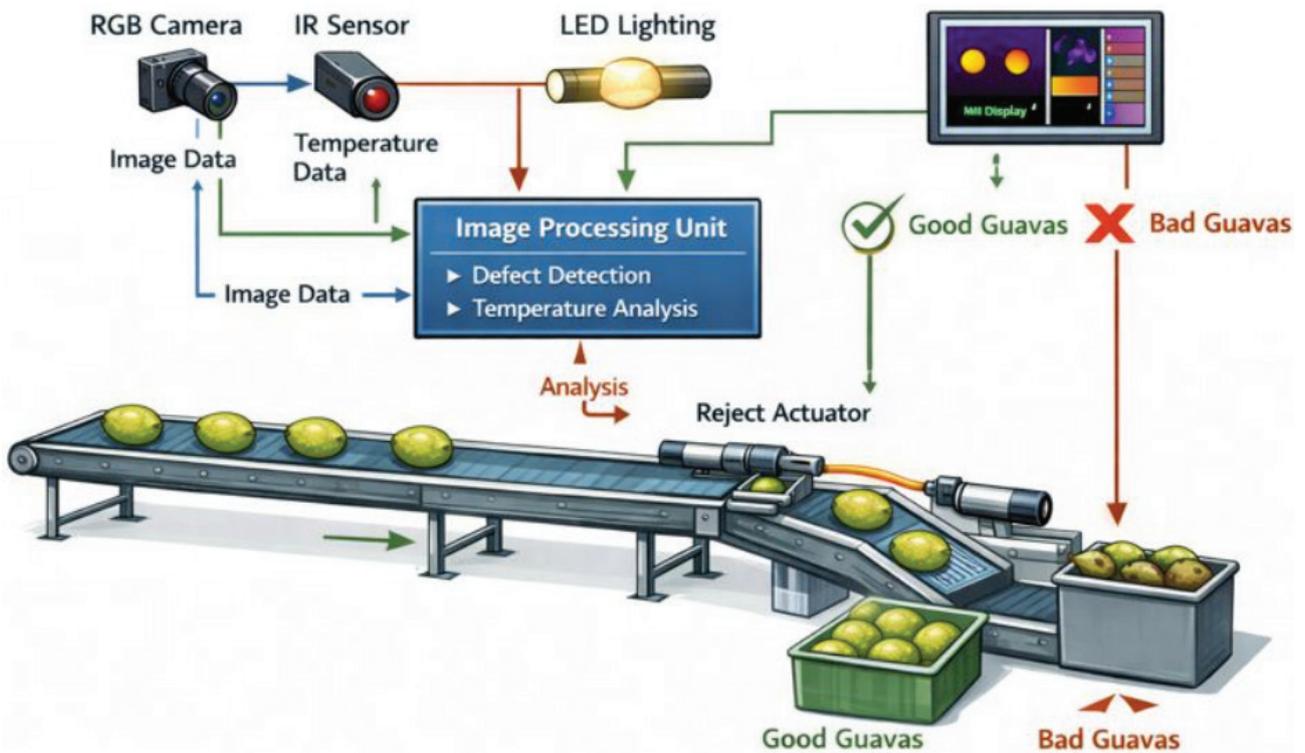
Figure 8. Inspection and segregation process.

a dashboard, control panel, alert/notification modules, real-time monitoring, data logging, and reporting features. The dashboard provides an overview of the status of the system, shows the number of fruits processed, quality metrics distribution, and live sorting, using visual representation like graphs and charts to facilitate understanding. The operators can begin, pause, or stop the sorting process as well as change system parameters through the control panel - such as illumination settings, camera calibration and sorting thresholds. The workflow of inspection and segregation is illustrated in Figure 8.

OUTLINE OF A MACHINE LEARNING ALGORITHM

The machine learning algorithm can effectively distinguish between Healthy Guava, Bird Eaten Guava, Physically Damaged, and Diseased guava types following the approach given:

1. Data Collection: Collect and label a diverse dataset of guava images.
2. Feature Engineering: Extract meaningful features such as color, texture, and shape.
3. Model Selection: Choose an appropriate model like SVM, Random Forest, or CNN.
4. Training: Train the model on the labeled dataset.
5. Evaluation: Assess model performance using accuracy, precision, recall, F1-score, and confusion matrix.

6. Optimization: Fine-tune the model to enhance its performance.

PLC Theory Used in Guava Separation

The sensors within the framework of this concept obtain the information related to guavas; the data obtained is then processed in a Programmable Logic Controller (PLC) to screen the fruit according to the established criteria. The PLC controls the sorting equipment, hence bringing to reality the segregation of guavas into separate categories. This way, consistency and accuracy of categorizing and sorting is reflected in the strength and reliability of PLCs in factories.

1. Sensors, Data Acquisition.

Varied sensors are installed to get information about the guava, these include, but are not limited to, chromatic sensors, morphological sensors and possibly crude imaging systems depending on whether they are compatible with the PLC. An example illustrating this is the color sensor is able to distinguish the color of a healthy guava and other colours that might indicate damage or pathology.

2. Signal Processing

The obtained raw data is processed to extract important information. This involves non-digital to digital representation, noise removal and normalizing the data set. With a color sensor, the PLC would be required to convert RGB values into understandable color measure that is amenable to classifications.

3. Feature Extraction

PLCs are coded to quantify certain qualities obtained out of the sensor data. An example would be the measurement of reflectance properties over the surface of the fruit, which would give information about the conformation of the fruit.

4. Decision-Making Logic

The logic, which is part of the PLC, categorizes the guavae based on the attributes that are extracted. The classification criteria are based on the thresholds or decision rules that are obtained as a result of sensor outputs. Strong sensitivity of the color sensor, say, might indicate the guava is sick, but abnormalities of the shape sensor might indicate physical damage.

5. Control Actions

Thereafter, the PLC controls actuators that separate the guava into different bins, healthy specimen in one bin, affected by the avian in the other, and so on, according to the categories applied.

6. User Interface

The PLC is also incorporated with a Human-Machine interface to provide real-time feedback and give the operators the leeway to either override or fine-tune the decision-making parameters. Precision, recall and confusion matrices are evaluation measures that are inevitable indicators of system performance and thus justifies the important inclusion.

Evaluation Metrics

1. Precision and Recall:

Precision: It estimates the exactitude of the positives being predicted. This is the ratio of correctly identified positive instances to the total number of instances classified as positive.

Recall: A measure that calculates the completeness of the positive predictions. It measures what proportion of positive instances are correctly identified from all actual positive instances in the dataset.

2. Confusion Matrix:

A confusion matrix is a table that gives the detailed breakdown of the system's predictions against the actual outcomes. It contains:

True Positive: Correctly classified high-quality guava fruits.

True Negative TN: Correctly classified low-quality guava fruits, if any.

FP (False Positive): those incorrectly classified as high-quality even though they are not. False Negative (FN): Misclassified as low quality while actually they are not.

RESULTS AND DISCUSSION

The 200 samples were carefully selected to represent various aspects of guava fruits that affect quality assessment. This selection process considered factors such as:

1. Size Variation: The dataset includes guava fruits of different sizes, ranging from small to large, to account for size-related quality attributes such as maturity and sweetness distribution.

2. Color Variation: Guava fruits exhibit a spectrum of colors as they ripen, from green to yellow and sometimes red or pink hues. The dataset encompasses this color diversity to train the system in identifying color-related quality indicators.

3. Defect Types: Common defects such as bruising, spots, cracks, and irregular shapes were included in the dataset. This ensures that the system is trained to detect and classify these defects accurately, which is critical for sorting out inferior quality fruits.

Representativeness

Samples were obtained in different sources as well as different production batches to cover a variety of geographical areas and cultivation environments to make sure that the dataset is representative. The approach eliminates bias and guarantees the trained model to generalise well within a range of guava varieties and agronomic practices. Strict quality-assurance checks were applied to each specimen to ensure the product is of the required size, colour, and defects. The system uses computer-vision algorithms to measure and categorize guava fruits as either healthy or defective (the latter that is, dinged, avian-eaten, or diseased fruit), based on the set criteria. There is sorting that is done based on certain parameters. The accuracy of system performance was checked through sorting and inspection of 200 specimens, which led to a 97 per cent correct determination of healthy and defective fruit. It involves the use of a conveyor belt and a segregating mechanism. Figure 9 illustrates a graphical form of the accuracy of the sorting trial. Comparative outcomes of the fruit categories are pointed out in Table 2.

The experimental outcomes show that, on average, throughout the stated quantity of trials, the guava sorting system was able to assign all the fruits to a relevant compartment, which, in its turn, would accumulate them in the

Table 2. Comparative results of fruits

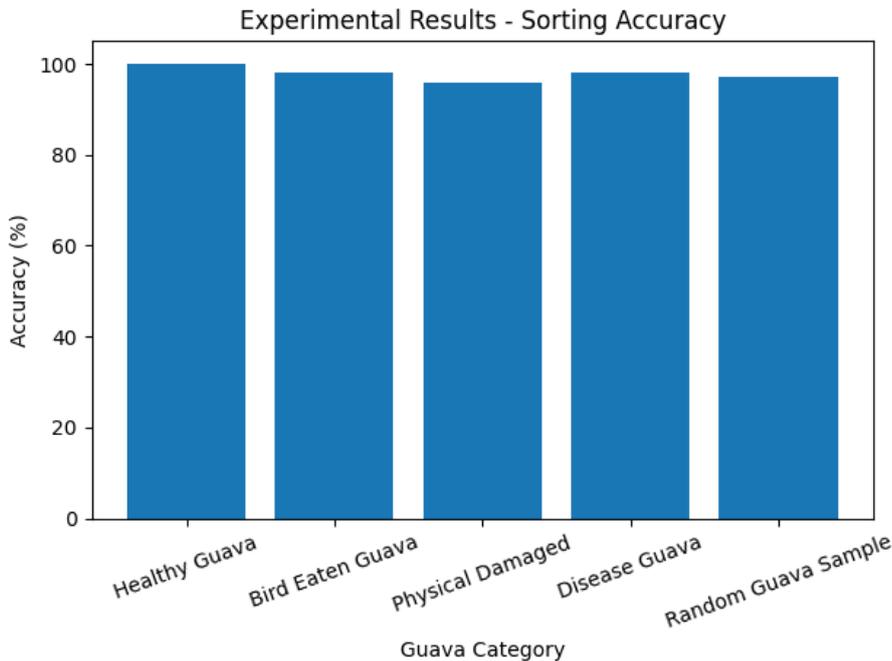| Sr No.	Type of Fruit quality tested	Total no. of fruit tested	Manual inspection results	Testing of developed system
1	Healthy Guava	50	50	50
2	Bird Eaten Guava	50	50	49
3	Physical Damaged	50	50	48
4	Disease guava	50	50	49
5	Random guava Sample	200	200	194

Figure 9. Graphical representation of accuracy percentage of sorting trial.

relevant baskets at the end of every sorting channel. The average time that it took to process each fruit was about 24 seconds and the inspection was in a continuous, consecutive manner where the items were positioned on the conveyor belt.

The suggested device works by identifying external texture features, thus separating and eliminating flawed guavas out of the conveyor belt. This could be used to improve quality control of products in the food-processing industry. To determine the performance of the system, there were four quality classes, namely healthy, damaged, bird-eaten, and diseased. Newly picked guavas of different grades were fed to the automated sorter and each batch was measured as per grading efficiency, production capability and percentage of defected fruits including those that were infested by birds and/or diseased.

Grading accuracy was measured by the rating of fifty specimen of each category of guava (healthy, damaged, bird-eaten, and diseased). The resulting efficiencies were 100, 98, 96 and 98 percent respectively of the healthy, bird-eaten, physically damaged and diseased groups. The grading efficiency when 200 guavas were randomly processed was at 97 on average. As a result, the constructed sorter has an adequate performance and its implementation may be expanded to various realm of spherical and oblate fruits at the farm level. The efficiency variation that was minor and was observed among three trials was attributed to manual loading of fruits.

A comparative evaluation of the intelligent sorter with the traditional manual or other automated processing devices shows that the new technology is superior in speed, accuracy, and flexibility to changes in size, colour and defect profiles. The use of multispectral/hyperspectral imaging and further analysis of images with the help of MATLAB in conjunction with PLC-controlled actuators will be a technological advancement to the conventional methods. The combination of real-time data processing, adaptative control approach, and machine-learning algorithms to assess quality will be estimated to result in increased accuracy. The expected benefits of operations are that they will be dependent less on manual labour, the sorting output will be consistent, the wastage will be reduced because of proper identification of defects, and the whole operation will save money in labor and quality maintenance.

The smart sorter, which is based on the advanced image analysis, is a modern solution to the fruit sorting, which is done based on their size, colour, and flaws. The high-resolution cameras and advanced machine-learning models make it possible to achieve proper segregation and, hence, reduce labour costs and improve throughput. The efficiency, accuracy, and productivity of agricultural sorting processes are increased since the users can comfortably monitor and manipulate the operations using a convenient interface. A heterogeneous and comprehensive set of data will be used to ensure that the system is not sensitive to real-life changes in guava morphology and condition to ensure that the system is robust and has the same performance across various batches and manufacturing conditions.

Wavelength differential detection theory is based on the concept of using differences in the spectral characteristics

of reflected or transmitted light to use between different classes of guava as healthy, bird-eaten, physically damaged, and diseased. The system categorizes the fruit using certain wavelength ranges by examining surface reflectance spectra that change depending on pigment composition, texture, and the moist content in the fruit. Multispectral or hyperspectral cameras are used to capture images in the visible (400-700nm), near infrared (700-1000nm), and short wavelength infrared (1000-2500nm) regimes. The spectral signature of every pixel is complete, and discriminative features, like the ripeness or the presence of a defect, may be extracted. Baseline signatures are set by calibration using reference samples, and spectral fidelity is increased by pre-processing, namely normalisation and noise reduction.

Thermal imaging is a technology that uses infrared thermography to identify temperature variations that are caused by internal and surface conditions to indicate defects like bird pecks, mechanical, or disease. Accuracy, precision, recall, and F1 -score are the performance metrics. The temperature contours in healthy guavas are symmetric, and thermal irregularities are observed in peck sites of fruits eaten by birds. Guavas that are damaged physically depict severe temperature variances near the areas of damages and unhealthy fruit displays wider temperature variances due to the variation in water content and metabolic activities. Thermographic data combined with machine-learning classifiers allows reliable defect-detection, which allows quality packing and distribution of products and avoids the need to inspect the product manually and enhances consumer satisfaction. In addition, it has the capability of early disease detection, and this means that intervention is done in time, preventing a loss in yield.

Main constraints of the existing system reside in the fact that the system relies on the constant illumination; changes to illumination may affect image segmentation and feature extraction, thus necessitating the additional expenses to obtain the necessary lighting infrastructure. Also, the system does not support irregularly shaped or partially covered fruits and thus will experience segmentation failures and misclassifications with large volume processing. The need to rely on high-resolution imaging devices and advanced electronics also raise the cost and maintenance requirements, making it difficult to implement in small or resource-based environments. The degradation of the hardware may affect the performance, and regular maintenance is required.

In an attempt to overcome these issues, further studies ought to be carried out to create illumination-invariant algorithms, use of adaptive thresholding, enhanced noise-reduction methods and dynamic and machine-learned illumination modulation. Multispectral imaging can be incorporated to enhance the resistance of the classification to changing light. Better segmentation techniques, including convolutional neural networks with more advanced topology, are to be considered in order to address complex shapes and occlusions. Finer shape and volume estimates can be given by three-dimensional imaging helping to sort finer. With the system, the accessibility can be made more accessible by cutting down on the high cost of hardware and customizing software to operate with low-cost cameras that are abundant in the market. Scalability will be enabled by lightweight, real-time enabled algorithms designed to fit to lower power devices, edge computing, and integration with IoT. Lastly, the user interface will be iteratively enhanced with the help of operator feedback to create increased intuitiveness and user satisfaction to make the implementation more widespread.

CONCLUSION

Feasibility studies indicated that the proposed design for a guava sorting machine was suitable for detailed development. Thermal cameras and other equipment proved effective in identifying and segregating healthy and defective guava fruits. Implementation of a belt conveyor helps prevent physical damage to fruits and improves the grading efficiency of the machine.

1. The developed sorting system is highly efficient in grading guava fruits and thus may serve beneficial for industries that require automatic sorting.
2. The effectiveness of grading by the proposed automatic sorting system was investigated using a testing machine with 50 guava fruits for each variety: healthy, damaged, bird-eaten, and diseased. The grading efficiency of the automated sorter with each quality sample of guava fruit variety was 100%, 98%, 96%, and 98%, respectively.
3. Sorting the guava into healthy and defective compartments with a grading efficiency of 97% was done for 200 guava samples.
4. The most appropriate conveyor speed was estimated to be 10.5 cm/s, considering the thermal camera's ability to accurately capture and analyze the image in MATLAB of one guava at a time. The time taken to carry one guava for sorting was 23 seconds.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article. ETHICS There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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