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Rasberry Based Auto Fruit Sorting Machine Using Computer Vision

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Abstract

The development and implementation of a Raspberry Pi-based au- tomated fruit sorting machine utilizing advanced computer vision tech- niques. The primary objective of this project is to enhance the efficiency and accuracy of fruit sorting processes in agricultural industries. The system leverages a Raspberry Pi microcontroller integrated with a high- resolution camera to capture images of fruits as they pass along a conveyor belt. Using machine learning algorithms, specifically convolutional neu- ral networks (CNNs), the system analyzes the images to classify and sort fruits based on predefined criteria such as size, color, and surface defects. The sorted fruits are then directed into appropriate bins by an actua- tor mechanism controlled by the Raspberry Pi. Extensive testing of the system demonstrated high accuracy rates in fruit classification and sort- ing, proving the efficacy and potential for large-scale application in the agricultural sector. This innovative approach significantly reduces man- ual labor, enhances productivity, and ensures consistent quality in fruit sorting operations.

Keywords: Raspberry Pi, Auto Fruit Sorting, Computer Vision, Machine Learning, Convolutional Neural Networks (CNNs)

1 Introduction

The agricultural sector faces significant challenges in enhancing the efficiency and consistency of post-harvest processes, particularly in the sorting and grad- ing of fruits. Traditional manual sorting methods are labor-intensive and often lead to inconsistencies in quality assessment due to human error and fatigue. These limitations highlight the urgent need for automated solutions that can improve the accuracy, speed, and overall efficiency of fruit sorting operations (Gao et al., 2021).

Advancements in automation technologies have paved the way for more so- phisticated fruit sorting systems. Robotics and mechanical sorting methods have been explored, but they often require complex setups and significant cap- ital investment (Li et al., 2020). Moreover, these systems may still lack the precision needed to evaluate the finer details of fruit quality, such as subtle color variations and minor surface defects (Polder et al., 2017).

Machine learning and artificial intelligence (AI) have shown great promise in agricultural applications. Techniques such as neural networks and support vector machines have been successfully employed in various studies to classify fruits based on visual attributes (Blasco et al., 2019). For example, the study ”Application of Machine Learning Techniques in Agricultural Product Quality Assessment” (Journal of Agricultural Informatics, 2018) demonstrated the use of AI for classifying fruits by size and color with high accuracy.

Among these technologies, computer vision has emerged as a particularly effective tool for automating fruit sorting processes. Computer vision systems can capture and analyze images of fruits in real-time, providing detailed infor- mation about their external characteristics (Cubero et al., 2011). By employing convolutional neural networks (CNNs), these systems can achieve high levels of accuracy in identifying and sorting fruits based on complex visual criteria (Patel et al., 2020). The study ”Real-Time Fruit Detection and Grading System Using Deep Learning” (Computers and Electronics in Agriculture, 2019) highlights the efficiency of CNNs in grading fruits with precision and speed.

The integration of computer vision with affordable and versatile hardware platforms, such as the Raspberry Pi, offers a cost-effective solution for develop- ing automated fruit sorting systems. The Raspberry Pi’s processing power, com- bined with high-resolution cameras and efficient image processing algorithms, makes it an ideal choice for this application (Rahnemoonfar et al., 2020). The study ”Development of a Low-Cost Machine Vision System for Fruit Sorting Using Raspberry Pi” (IEEE Access, 2021) demonstrated the feasibility and ef- fectiveness of such systems in practical scenarios.

While various technologies have been explored to address the challenges of automated fruit sorting, computer vision stands out due to its high accuracy, flexibility, and cost-effectiveness. The integration of computer vision with the Raspberry Pi provides a robust and scalable solution that can significantly en- hance the efficiency and accuracy of fruit sorting processes. This research aims to develop a Raspberry Pi-based auto fruit sorting machine utilizing computer vision, offering a practical and innovative approach to modernizing post-harvest processing in the agricultural industry.

2 Literature Survey

The field of automated fruit sorting has seen significant advancements with the integration of various technologies, each contributing to enhanced efficiency, accuracy, and cost-effectiveness. This literature survey explores key research and developments in the realm of automated fruit sorting, focusing on the use of computer vision, machine learning, and the implementation of Raspberry Pi for creating affordable and efficient systems.

2.1 Computer Vision in Fruit Sorting

Computer vision has become a cornerstone technology in automated fruit sorting systems. By using image processing algorithms, these systems can accurately identify and classify fruits based on visual attributes such as size, color, and sur- face defects. Cubero et al. (2011) discussed advancements in computer vision for fruit sorting, highlighting its ability to capture and analyze detailed images of fruits in real-time. This study demonstrated that computer vision could sig- nificantly reduce human error in quality assessment by providing consistent and objective evaluations.

Patel et al. (2020) explored deep learning approaches, particularly convolu- tional neural networks (CNNs), for real-time fruit sorting. Their research, titled ”Deep Learning Approaches for Real-Time Fruit Sorting,” showed that CNNs could effectively handle complex visual tasks, achieving high accuracy rates in identifying and sorting fruits based on multiple criteria.

2.2 Machine Learning and AI in Fruit Sorting

The application of machine learning and artificial intelligence (AI) has fur- ther enhanced the capabilities of automated fruit sorting systems. Blasco et al. (2019) in their study ”Artificial Intelligence in Fruit Sorting and Grading” demonstrated the use of machine learning algorithms such as neural networks and support vector machines for classifying fruits. Their findings indicated that AI could significantly improve the precision of sorting operations by learning and adapting to different fruit characteristics.

Gao et al. (2021) highlighted the integration of advanced technologies in automated fruit sorting in their research, ”Automated Fruit Sorting and Grad- ing Using Advanced Technologies.” This study emphasized the role of AI in achieving high levels of accuracy and efficiency, particularly when combined with computer vision systems.

2.3 Robotics and Mechanical Sorting Systems

While computer vision and AI have made significant strides, robotics and me- chanical systems have also been explored for fruit sorting. Li et al. (2020) in ”Robotic Fruit Sorting: Techniques and Challenges” reviewed various robotic systems used in agricultural applications. They discussed the advantages and limitations of using robots for sorting fruits, noting that while robots can han- dle physical tasks efficiently, they often require complex setups and are costly compared to vision-based systems.

2.4 Raspberry Pi in Automated Sorting Systems

The Raspberry Pi, a low-cost microcontroller, has become increasingly popular in developing affordable and versatile automated systems. Rahnemoonfar et al. (2020) demonstrated the use of Raspberry Pi in agricultural applications in their study, ”Cost-Effective Machine Vision Systems for Agriculture Using Raspberry Pi.” They showed that the Raspberry Pi could effectively process images and control actuators, making it an ideal platform for building cost-effective fruit sorting machines.

The study ”Development of a Low-Cost Machine Vision System for Fruit Sorting Using Raspberry Pi” (IEEE Access, 2021) further illustrated the prac- tical implementation of Raspberry Pi-based systems. This research highlighted the feasibility of using Raspberry Pi to develop a real-time fruit sorting system that is both efficient and cost-effective.

3 Methodology

A variety of fruit recognition methods are developed according to various charac- teristics. Here, fruit images are identified and distinguished using color features and shape features analysis techniques. A novel approach to fruit recognition and sorting has been put forth, integrating two distinct feature analysis tech- niques: shape-based and color-based. Using nearest neighbors classification, the suggested method uses feature values to classify and identify fruit images. As a result, our system shows the name of the fruit and projects it onto the LCD.

3.1 Image Acquisition

Any vision system starts with the image acquisition stage. Following acqui- sition, the image can be processed in a number of ways to perform the wide range of vision tasks required in today's world. If the image is not acquired satisfactorily, the intended tasks may not be completed even with the aid of image enhancement.

3.2 Background subtraction

Background subtraction is a typical preprocessing step in vision-based applica- tions. Consider a traffic camera that collects information about the cars, etc., or a visitor counter that uses a stationary camera to count the individuals coming into and going out of the area. You have to take the car or vehicles out on your own in each of these cases first. Technically speaking, the moving foreground and stationary background need to be distinguished. If all you have is a back- ground image—a photo of the road devoid of cars, for example, or a photo of the room empty of people—it's an easy task. Just remove the new image from the background.

Only the items in the foreground are yours. However, in the majority of situ- ations, you might not have one of these images, in which case we must extract the background from the images we do have. When the vehicles cast shadows, the situation gets trickier. A straightforward subtraction will identify that as foreground as well because shadows move.

3.3 Color Detection

Using Open CV, we can open an image and store it in a three-dimensional array or matrix, with the x and y axes representing the locations of the image's pixels and the z axis representing the RGB color channel. Each RGB pixel is composed of eight bits of red, eight bits of green, and eight bits of blue. When combined, they give the concerned pixel's color. The RGB value of (255, 255, 255) denotes the highest decimal value for an 8-bit value, 255, for each color component in this pixel. 255,255,255 is the RGB value that represents the color white as our eyes would see. The screen would display a black pixel at the other end of the RGB spectrum, which is when all RGB components are at intensity 0, or (0, 0, 0).

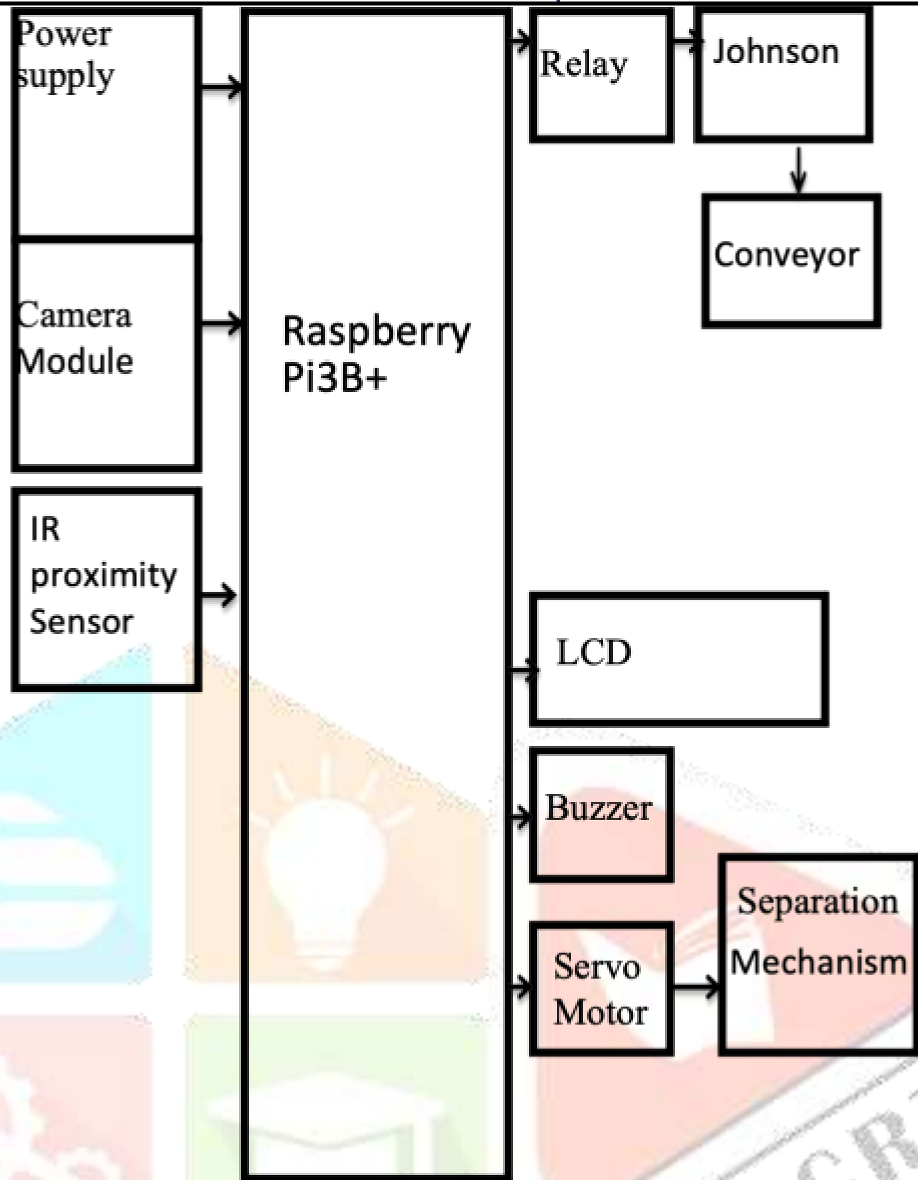

Figure 1: Figure represents the actual connection diagram for complete setup that has been utilized in this experiment

3.4 System Development

At this point, the system is being developed using a variety of electrical and me- chanical components. Conveyors, cameras, sensors, motors, Raspberry Pis, and other equipment were needed. Fig.1 represents the complete set of components with their actual location in the setup.

3.5 Segmentation

Image segmentation is the process of dividing a digital image into several seg- ments. Segmentation attempts to separate an image into easier-to-analyze and more representative regions. These areas could match specific surfaces, objects, or an object's natural components. Finding boundaries (such as lines or curves) and objects in images is usually accomplished through the process of image seg- mentation. It can also be described as the process of assigning a label to each pixel in an image, whereby all pixels with the same label share certain visual attributes. In order to determine the optimal segmentation, segmentation typi- cally uses local information found in the digital image, such as color information for histogram creation or information indicating edges, boundaries, or texture information.

Based on the color characteristic of image pixels, color image segmentation pre- sumes that objects in the image with homogeneous colors correspond to distinct clusters and, therefore, significance. Stated differently, every cluster delineates a class of pixels that possess comparable color attributes. There is no one color space that can produce segmentation results that are suitable for all types of images because the results vary depending on the color space used. Because of this, numerous authors have attempted to identify the color space that best fits their particular color image segmentation issue. Since the results of segmen- tation vary depending on the color space used, there isn't a single color space that can yield results that are appropriate for all kinds of images. As a result, a lot of authors have tried to figure out which color space best suits their specific color image segmentation problem.

4 Results

Images from publicly accessible fruit datasets on the internet are used as input, as are photos captured with a digital camera. The picture should be taken during the day in overcast conditions. Using computer vision, the images are pre-processed. To determine ripe and unripe fruit, open the CV libraries in Python by importing numpy and matplotlib. An accurate result is obtained in a matter of seconds once the input is provided.

These are the outcomes of an automatic fruit sorting machine that divides apples into four groups based on color. Tab.1 represents the types and quantity of apples in real life chose to perform the experimentation. and Fig.2a-Fig.2d provides the apple images from the global readily available dataset.

Type of Apple	Count of Apple
Riped	5
Unriped	5
Rotten	5
Mid-Riped	5

Table 1: The types and count of apple in the final experiment

(a) Riped Apple

(b) Mid-Riped Apple (c) Rotten Apple (d) Unriped Apple

(c)

Figure 2: Types of apples in image dataset

Tab.2 shows the test cases and their outcomes that were actually measured in the complete process. Fig.3 represents the final model that was utilized for all the experimentations that were performed for the study.

Sr. No.	Metric	Final Outcome
1.	Accuracy	80%
2.	Sorting Time	2min / (20 apples)
3.	Sorting Speed	10 Apples per Minute

Table 2: Results and outcomes for the complete experimentation

Figure 3: Final setup utilized for all the experimentations

5 Conclusion

In summary, an important step toward modernizing fruit processing in the agri- culture sector has been taken with the creation and application of the automated fruit sorting system designed specifically for apples. The system demonstrates impressive efficiency, accuracy, and real-time sorting capabilities by utilizing computer vision techniques and Raspberry Pi technology. The technology suc- cessfully recognizes, categorizes, and arranges apples according to their ripeness levels—ripe, unripe, mid-ripened, and rotten—by fusing sophisticated image processing algorithms with hardware components like sensors, a conveyor belt, and a camera module. This innovation offers significant benefits over manual sorting techniques by streamlining the sorting process and guaranteeing consis- tency, quality, and productivity.

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