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Development of Fruits Artificial Intelligence Segregation

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ABSTRACT

Higher output was needed as technology advance to meet human needs and industry demands. Fruits Artificial Intelligence Segregation (FAIS) is a project that uses image processing to detect and differentiate between various types of fruits. This paper proposes an OpenCV python, and the Convolution Neural Network (CNN) is used to complete the segregation of multiple fruits. The code extracts the fruit's characteristics and separates them based on their color and shape once placed in front of the camera to implement liveness detection. This paper shows the accuracy and reliability of the Fruits Artificial Intelligence Segregation (FAIS) system based on the number of datasets.

Keywords: Artificial Intelligent, Open VC, tensor flow, Raspberry Pi, image recognition

1. INTRODUCTION

To meet human needs and the market, the digital transformation of technology needed higher efficiency. This project is modified to make human work more accessible and, due to future applications of AI, will reduce the use of human resources. This Fruit Artificial Intelligence Segregation (FAIS) is used to classify and recognize different fruit. The Artificial Intelligence (AI) algorithm will work in such a way where a group of fruit is placed under the camera, the system will distinguish the fruits according to their colour and shape. The working algorithm and its function will be described in detail in this paper. In short, the algorithm will use the python library to evaluate the fruit colour and shape (OpenCV, tensor flow, Keras, CNN).

As far as the application in agriculture such as fig fruit plantation is concerned, it is recognized that the system will benefit in this kind of industry. The system can be placed in the post-harvest process, such as processing agricultural products and sorting the fruits before the subsequent storage or delivery process. This method also involves washing, sorting, grading, and packaging. Sorting and grading are post-harvest processes that classify products based on the quality-determining appearance, size, and shape of food products. Human experts often perform sorting, but more difficult is the method of time-taking. To satisfy human needs and the market, the growth of technology needed higher efficiency [1-2]. This project is being introduced to make human work simpler and, because of its possible applications, will reduce the use of human resources.

2. FRUIT SORTING SOLUTIONS

Fruits are in various shapes, colours, and sizes. There are also subtypes of fruit in the same family, such as for apples, there are Granny Smith, Fuji, Pink Lady, and another 100 more types. In this work, the significant shape of the fruit is focused on rather than defining the fruit's subtypes. Thus, the types of fruits that will be sorted will be based on the images in the databases.

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CNN is an excellent tool to solve this problem due to its ability to remove relevant features from images without a comprehensive, advanced engineering method. However, a lot of data are required for a CNN to extract the information in each dataset. Therefore, more information is needed during the model's training for the algorithm to extract the necessary features for a particular fruit.

3. LITERATURE REVIEW

U. Dorj, M. Lee, and S. Yun (2017) estimated the orchard yields by adoption and categorized the fruit by AI [3]. Many steps are used in the algorithm, including converting red, green, blue (RGB) to hue-saturation-brightness (HSV), entering a threshold, obtaining an orange color, removing the noise in achieving a better image recognition. The integrated fruit count algorithm and the fruit creation rate by flower counting are also compared in their work. Their experiment findings revealed that the algorithm for detecting and counting lemons using hybrid change could be implemented in various ways. In summary, the authors have highlighted that this algorithm for detecting and measuring the lemon fruits of an orange family using an extraction method has been found to be accurate and reliable.

DhameshwariSahu and Ravindra M. P (2017) use computer vision applications and image processing for identification and consistency assessment in agriculture applications [4]. Fruit defect detection and identification is a challenging task to accomplish near-human levels of detection. The authors create a structure that is beneficial to the seller and can be used to apply computer vision to the automated separation of fruits from various types of fruits. Using digital image processing, the authors created a method to detect defects and determine the ripeness of fruits based on their size and shape elements.

Bhargava and A. Bansal (2018) established their most recent research on fruit and vegetable quality assessments using a monitoring system [5]. The technique was developed, including pre-processing, categorization, fruit, and vegetable extraction based on different compositions and classification. The paper also discussed a study of different quality assurance, ultrasound, infrared imaging, and tomographic imaging concepts proposed by analysts.

In this paper, the use of the CNN method is further explored due to the better image accuracy than RGB color detection.

Table 1 Comparison between RGB and CNN techniques

RGB Color detection	**Convolutional Neural Network, CNN**
Set the lower and upper threshold values (in HSV format). Use the cv2.inRange method to get the HSV values between the lower and upper range [6].	Using the Keras (v2.0.6) library with TensorFlow (v2.2.0) backend for Python 3.8 to access image database in the programming language. The image database is also known as a training image. The training image contains numerous fruits' angles and colours (freshness) to act as a database [7].
Less accurate because affecting factors towards the brightness of the environment.	Convolutional Neural Network CNN technique is more accurate compared to the RGB Colour detection technique.

4. METHODOLOGY

4.1 Software Tools

The CCN techniques applied in this work use several two main software: Phyton 3.8 and OpenCV.

4.2.1. Phyton 3.8

Python is a flexible language for programming that is easy to understand. These have successful high-level knowledge structures and a simple but efficient approach to object-oriented programming. For all major platforms from the Python Web site, a python interpreter and the full standard library are freely available and can be freely distributed in source or binary form. The same section also provides distributions and pointers to some free Python third-party modules, programs and tools, and additional documentation.

4.2.1. OpenCV

The Open-Source Computer Vision Library (OpenCV) is an open-source computer vision and machine learning software library. Over 2500 optimized algorithms in the library include a broad set of computer vision and machine learning algorithms, both classic and state-of-the-art. These algorithms can be used to identify and recognize faces, identify objects, classify human activity in videos, monitor camera movements, track moving objects, extract 3D object models, generate 3D point clouds from stereo cameras, stitch images together to create a high-resolution image of the entire scene, check for an identical image from an image database, and delete red eyes from a flash image.

4.2 Hardware Tools

Below are the hardware used in this project.

4.2.1 Raspberry Pi3B+

The 3rd generation Raspberry Pi is the Raspberry Pi 3 Type B+. This powerful single-board credit-card-size device can be used for several uses and replaces the Raspberry Pi 3 Model B+. The model B of the Raspberry Pi 3 offers a more robust process, 10x faster than the Raspberry Pi first generation, while maintaining the standard board shape.

4.2.2 Raspberry Pi Camera

RPI camera board plugs are directly connected to the CSI connector on the Raspberry Pi. The new v1.3 offers a crystal clear 5MP resolution image or 1080p HD video recording. In addition, the board features a Univision 5647 5MP (2592 to 1944 pixels) module with a fixed focus on the image.

4.3 Image Analysis

4.3.1 Image Acquisition

To acquire the image, one must first set up a black or proper dark background for the fruit and place it directly under the camera of the Raspberry Pi. For a good picture to be captured, excellent and bright lighting is a must. After that, the video frames are returned constantly until the live video stream starts from the camera.

4.3.2 Image Pre-Processing

First, the image frame is resized according to the needs after the returned image is obtained. It helps in removing the high-frequency elements from the image (e.g., sounds and edges). In this project, the Gaussian Blur kernel is used to filter the high-frequency components, which will make the image blurry. Next, the image is converted from an RGB to an HSV model. After that, the section of the image has values in the described range are segmented. After these segmenting processes, if the image still has some noise, the image f further filtered using morphological operations. To perform such an operation, a matrix of one (i.e., a kernel) is needed. The kernel is used to perform dilation operations and erosion on the images. Both steps need to be done in sequence. If not, the background noise is removed. In general, image processing involves three stages: image acquisition methods, analyzing and changing the image, and finally, performance, resulting in alteration of the image or report based on image analysis.

4.3.3 Colour Detection

For the color of fruits, the acceptable threshold values are identified and stored in the dictionary. The values are in the form of HSV values. The values are given along with the color keys. The processing loop only goes forward in the frame and contains specific values between the key's lower and upper threshold values.

4.3.4 Detecting the fruit and display the Result.

Based on the contour and key, the fruit type is detected. Next, a circle around the fruit with a certain radius is drawn, and the core coordinates are calculated from the above measurements. Finally, a text is shown, indicating the fruit's name. In this way, the fruits have been sorted.

4.4 Image Processing Concept

4.4.1 Gaussian Filter

Gaussian filtering is performed by combining each point with a Gaussian kernel in the input array and then summarizing them to generate the output array. The filter used is the Low Pass type. It is helpful in extracting the picture from high-frequency components (e.g., noises and edges).

4.4.2 Kernel

A kernel is a small matrix that slides across a larger image from top-to-bottom and left to right. The neighborhood of the image is convoluted with the kernel at each pixel in the input image, and the output is processed.

4.4.3 Morphological Transformation

Some significant operations based on the image shape are morphological transformations. It is also generally executed on binary images. One is our original image, and the second is called the structuring factor or kernel that determines the nature of the operation. Two inputs are necessary. Erosion and dilation are two simple morphological operators.

4.4.4 Erosion

Through the picture, the kernel slides (Similar to 2D convolution). A pixel (0 or 1) only 1 is considered in the original image if all the pixels below the kernel are 1. Otherwise, 1 is eroded (made to zero). Likewise, all the pixels near the boundary will be discarded, depending on the size of the kernel. Thus, in the picture, in the white zone, the thickness or size of the foreground object decreases or decreases. It helps minimize small white noises.

4.4.5 Dilation

At this stage, when at least one pixel is '1' under the kernel, a pixel element is '1'. Thus, it increases at the white region of the image or increases the foreground object's size, and it is often helpful for connecting the broken pieces of an object.

4.4.6 Opening

Opening is another phrase, after dilation, of erosion. It removes small pixels from the background of an image and placing them in the background

4.4.7 Closing

Closing, accompanied by erosion with dilation, is the opposite of opening. It used to remove the small pixels/holes of the obtained image. Generally, it is used to smoother the contour of the distorted image.

4.4.8 Contours

It is simply possible to define contours as a curve of the same color or strength linking all the straight points (along the boundary). For form analysis and artifact detection and recognition, the contours are a helpful method for object detection and recognition.

5. RESULTS AND DISCUSSION

Figure 2. Detection of Apple and Orange

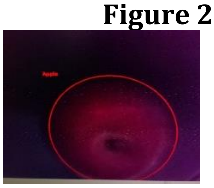

Figure 3. Detection of Apple - initial

Figure 4. Detection of Apple - final

Figure 2 to Figure 4 shows the detection using FAIS. The created algorithm recognizes the fruits from a live camera. Here the algorithm is tested, for simplicity of detection, by using two types of different fruits: apple and orange. FAIS algorithm evaluates the quality attributes such as form, scale, color, and other external characteristics. It is used to capture and collect pictures of the real world. Collecting the information in symbolic or numerical meaning requires image collection, pre-processing, analyzing, and interpreting the sample images. To assess the acceptability of the solution, consistency in preparation, validation and test sets will be used.

FAIS is used to detect and differentiate between various fruit forms. This study implements liveness detection techniques on the fruit segregation system. This study includes all the comprehensive descriptions of the components used in the AI operation. To distinguish the fruits from an image, a convolutional neural network has been implemented. Convolutional neural networks have been tested and found to be the best approach for image classification.

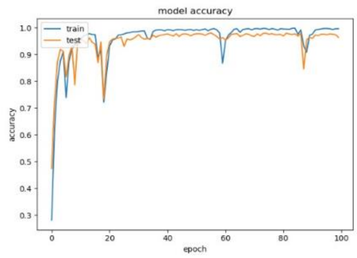

Figure 5. CNN Model accuracy curves during the 100-epoch training process for randomly selected 20% of image dataset to train.

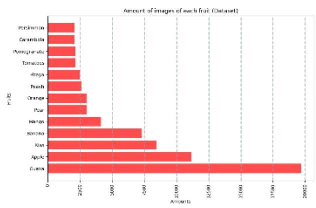

Figure 6. The distribution of fruit as the dataset.

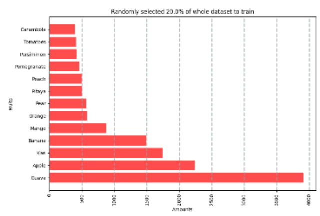

Figure 7. Random selected 20% of the image dataset to train.

Figure 6 shows the distribution of fruit as a dataset with various pictures, such as groupings of fruits, varied sceneries, and no fruit detection were employed in the study. Initially, images were divided into categories and supplemented with additional samples, yielding around 150 thousand images. Then, the model was trained using a random sample of 30 thousand images (20%), as shown in Figure 7. Sequential CNN model with kernel and tensor flow as activation function was used. To satisfy the needs in the agriculture-related industry, advancement in AI technology is needed for higher sorting efficiency.

Table 2 Classification accuracy on the test data using difference epoch.

Image dataset to train	Epoch	Classification accuracy on the test data
30 thousand images (20%)	100	99.81%
30 thousand images (20%)	75	98.91%
30 thousand images (20%)	50	97.88%

CNN Fruit AI Segregation (FAIS) classifier reached 99.81% classification accuracy on the test data in 100 epochs of training, which was very encouraging. An epoch is a unit of time used to train a neural network using all the training data for a single cycle. Use all the data exactly once in an era. A forward and backward pass are combined to make one pass: An epoch is made up of one or more batches in which we train the neural network using a portion of the dataset. The initial (test) was to verify if the changes towards the epoch would impact the model accuracy. The parameters that were observed and recorded for the epoch were 100, 75, and 50. The fixed variable was the data set of 20% throughout the epoch test. Table 2 shows that increasing the number of epochs improves the classification accuracy based on a fixed number of datasets.

Table 3 Classification accuracy on the test data using different Image datasets.

Image dataset to train	Epoch	Classification accuracy on the test data
30 thousand images (20%)	50	97.88%
60 thousand images (40%)	50	98.01%
90 thousand images (60%)	50	98.87%

After concluding the practical value for the epoch, the subsequent changes that were made were on the data set % with the fixed variable being the (50 epoch). Thus, the tested parameters for the data set were 20%, 40%, and 60%, while the fixed variable was the epoch set to 50. The outcome of this test is tabulated as in Table 3, which shows that increasing the image dataset to be trained, which consequently improves the classification accuracy based on a fixed number of epochs.

6. CONCLUSION

In this paper, FAIS using CNN has been successfully implemented. This method can implement the liveness detection techniques on the fruit segregation system using software, in which the sorting detection is performed by the shape and color of the fruit. A series of the test have been made towards the value of epoch and data test. The initial (test) was to verify if the changes towards the epoch would impact the reliability. The parameters that were observed and recorded for the epoch were 100, 75, and 50. The fixed variable was the data set of 20% throughout the epoch test. After concluding the effective value for the epoch, the following changes that were made were on the data set %, with the fixed variable being the 50 epochs. Thus, the tested parameters for the data set were 20%, 40%, and 60%, while the fixed variable was the epoch set to 50. The outcome of this test is shown in Table 1 and Table 2. This process is intended for an effective fruit segregation process, which will make the process automated and faster.

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