An Automated System to Classify the Maturity Status of Papaya Fruits Based on Transfer Learning Approach

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***Abstract*—Papaya (*Carica papaya*) is a delicious fruit with high medicinal and nutritional value, making it in high demand both as a fruit itself and in various papaya-based products, *viz.*, beverages, pharmaceuticals, and jam. Hence, increasing the volume and the quality of those products is essential. One of the main barriers to increasing the productivity of papaya-based products and papaya packaging is sorting out the fruit manually according to its maturity status. Manual sorting is highly time-consuming and expensive. One of the best solutions to overcome this issue is the automation of the process using machine learning (ML) techniques. In this project, an efficient conveyor system has been developed with the support of image processing and a transfer learning approach. For training a CNN, a dataset consisting of 1109 images of over-mature papayas, 1054 images of mature papayas, and 1367 images of immature papayas were used. Models of EfficientNetV2B1, MobileNetV3, ResNetRS50, and VGG19 were used to train CNN. Among these models, MobileNetV3 exhibited the best performance, with an accuracy of 100% within 10 epochs and a loss of 0.006%. EfficientNetV2B1 also exhibited 100% accuracy. However, the loss was 0.31%. ResNetRS50 reached 100% accuracy, and the loss was identified as 0.54%. The lowest performance was exhibited by VGG19. Though its accuracy reached 100% within 30 epochs, the loss was 151.37%. Therefore, MobileNetV3 was identified as the most accurate model to classify the maturity status of papaya fruits.**

Keywords—Automated system, image processing, machine learning, maturity status, papaya fruit, transfer learning approach

I. INTRODUCTION

Papaya (*Carica papaya*) is a delicious fruit that contains a high nutritive and medicinal value. It has been proven that papaya can reduce heart disease threats and prevent the oxidation of cholesterol since it contains antioxidants like vitamin A, vitamin C, and vitamin E [1]. Fiber in the fruit also helps to reduce cholesterol, thereby decreasing the threat of heart problems. Papaya not only decreases heart disease but also helps with digestion and decreases inflammation; hence, it contains papain and chymopapain enzymes. Moreover, vitamin C content boosts the immune system. As a tropical fruit that grows in Asian countries, a wide range of varieties, including Guinea Gold Papaya, Hawaiian Sunrise Papaya, Hawaiian Sunset Papaya, Hortus Gold Papaya, Kamiya Papaya, Kapoho Papaya, Oak Leaved Papaya, Peterson Papaya, etc., can be identified [2, 3]. In Sri Lanka, there are inherited varieties like Red Lady, Horana Hybrid, and Rathna. Generally, there is a yield of 60-100 metric tons per hectare per year from these verities in Sri Lanka. Due to its medicinal value and high yield throughout the year, papaya has a great global market value and industrial value as a fruit as well as processed products including beverages, jam, cordial products, chewing gum, soap, toothpaste, pharmaceuticals, and tanning [2, 3].

Due to these reasons, it is crucial to promote papaya cultivation, foster innovation in papaya-based products, and facilitate the exportation of both papaya fruit and papaya-derived processed goods. To dominate the local and international market for papaya, it is essential to increase the efficiency of production and maintain a high-quality margin. Therefore, an automated system for maturity status identification of papaya based on machine learning can play a significant role. Automating a sorting process can maintain quality and increase the efficiency of the process more than manual sorting since the automated system can work for 24 hours without taking a break [4]. Also, it can play a crucial role in mitigating the occurrence of damages during a manual sorting process. By reducing unnecessary labourer costs, manufacturers can produce quality products at the lowest possible prices. Therefore, it is a clear fact that this type of automated system can play a vital role when competing in the international market as well as the local market by maintaining high quality and high production efficiency. Due to these reasons, this project focuses on implementing a machine-learning-based papaya classification system according to their maturity status.

At present, in the manufacturing industry, artificial intelligence (AI) is used almost everywhere, owing to its capacity to process a vast amount of data, provide accurate predictions, and have self-learning abilities [4]. Mainly, fruit preprocessing industries use machine learning (ML, a subcategory of AI technology) base systems to sort out different fruits, classify fruits according to their maturity status, identify damaged and deformed fruits, etc. This project uses supervised learning: convolutional neural networks (CNN), since CNNs are best for solving computer vision-related problems and have higher feature extraction compatibility. Furthermore, the transfer learning (using a pre-trained model to solve the different problems) approach is used in the project.

II. METHODOLOGY

The methodology can be divided into three main stages: training and fine-tuning the ML algorithm, implementation of the prototype conveyor system for sorting papaya, and implementation of the graphical user interface (GUI). The overall workflow of the system is shown in Fig. 2.

A. Training and fine-tuning the ML Algorithm

1). Data Collection

For collecting images of papaya in order to create a training dataset, an A4tech PK-910H web camera was used. This full HD camera boasts a resolution of 1920 × 1080 pixels and operates at a frame rate of 30 fps. In order to prevent disturbance of exterior light sources a cover and a stand with a height of 0.5 m were occupied. Inside the cover, two bar lights with a temperature of 5500 K were employed as the primary light source. The front lighting method was adopted, providing an illuminance level of 170 lux inside the cover.

2). Data Categorization

When training a CNN using a supervised learning method, the training data set should be divided into intended categories. During the learning process, CNN adjusts its weights according to similar patterns in the given categories [5]. Accordingly, in this project, the collected papaya image data set has been manually divided into three categories and put into three files under the labels 0, 1, and 2. File “0” contained the immature papaya category; file “1” contained the mature papaya category, and file “2” contained the overly mature papaya category. This categorization was done based on the outer skin color of the papaya fruit, as shown in Fig. 1.

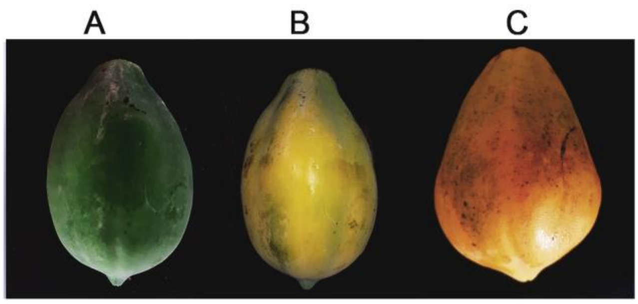

Fig. 1. Sample papaya fruit images collected. (A) Immature, (B) Mature, and (C) Over-mature.

3). Data Cleaning

In the collected data set, there was depraved data, or, in other words, corrupted pictures like blurred pictures, pictures with unwanted background noise (like objects in the background and light spots), and images with imprecise sizes. When training the neural network, this kind of depraved (or bad) data adversely affects the accuracy of the predictions since those images cause unnecessary changes in weights. Therefore, the depraved data was removed to obtain better performances. Also, the image categories were revisited, and mismatched images were removed. For instance, there can be images of mature papayas in the immature category or in the over-mature category, which can adversely affect the accuracy of the model. Further, the data set was revisited several times, and confusing images like images with bad lighting and images with a few or a portion of papaya instead of one were cleaned in order to enhance the accuracy of the model.

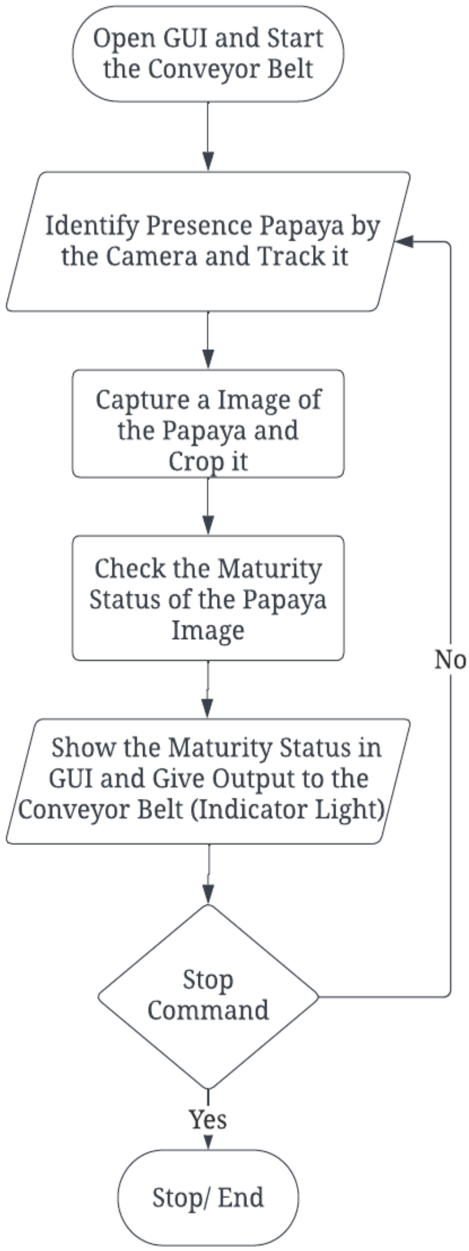

Fig. 2. Workflow of the system

4). Implementation of ML Algorithm

Python was chosen as the programming language for implementing the ML algorithm since it is a high-level language with flexibility and simplicity. The transfer learning approach, which uses pre-trained CNN models for retraining to find a solution to the intended problem, has been used. The pre-trained models EfficientNetV2B1, MobileNetV3, ResNetRS50, and VGG19 were considered [6]. The final layer of those pre-trained CNN models was changed to obtain the intended output, which has three (03) categories (immature, mature, and over-mature). Thresholding and background subtraction methods were used to identify the presence of papaya fruit on the conveyor belt. In the implemented system, as the papaya fruit moves along the conveyor belt, the camera captures images containing papaya fruit, which can be detected using threshold values as shown in Fig. 3.

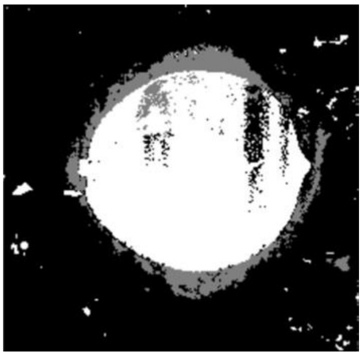

Fig. 3. Background subtraction

B. *Implementation of the Prototype Conveyer System.*

To run the conveyor belt, the stepper motor (NEMA17 17HS4401), which has a holding torque of 280 mN/m, was used, and the TB6600 Arduino stepper motor driver was used to control them. Overall, the combination of a NEMA17 stepper motor and a TB6600 Arduino stepper motor driver is a powerful and reliable solution for applications where precise positioning and control are important. The A4tech PK-910H web camera was used for capturing the images. It has a high-definition resolution of up to 1920 × 1080 pixels. It has a wide viewing angle of up to 80 degrees, allowing it to capture a large area in front of it. Further, for implementing the main unit and serial communication, an Arduino Uno board based on the ATmega328p microcontroller was used. Finally, three (03) indicator lights were occupied in the hardware setup to indicate the maturity status of the papaya fruit, as shown in Fig. 4.

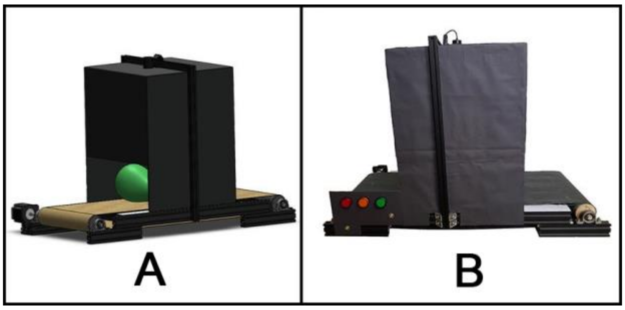

Fig. 4. (A) 3D Model of the conveyor belt system and (B) Conveyor belt system built for the project.

C. Graphical User Interface (GUI)

Tkinter is a Python library that is used for creating graphical user interfaces (GUIs). It is a standard GUI library for Python and is included with most Python installations. Tkinter provides a set of tools for building and customizing graphical interfaces, including buttons, labels, text boxes, and other widgets. The implemented GUI is shown in Fig. 5.

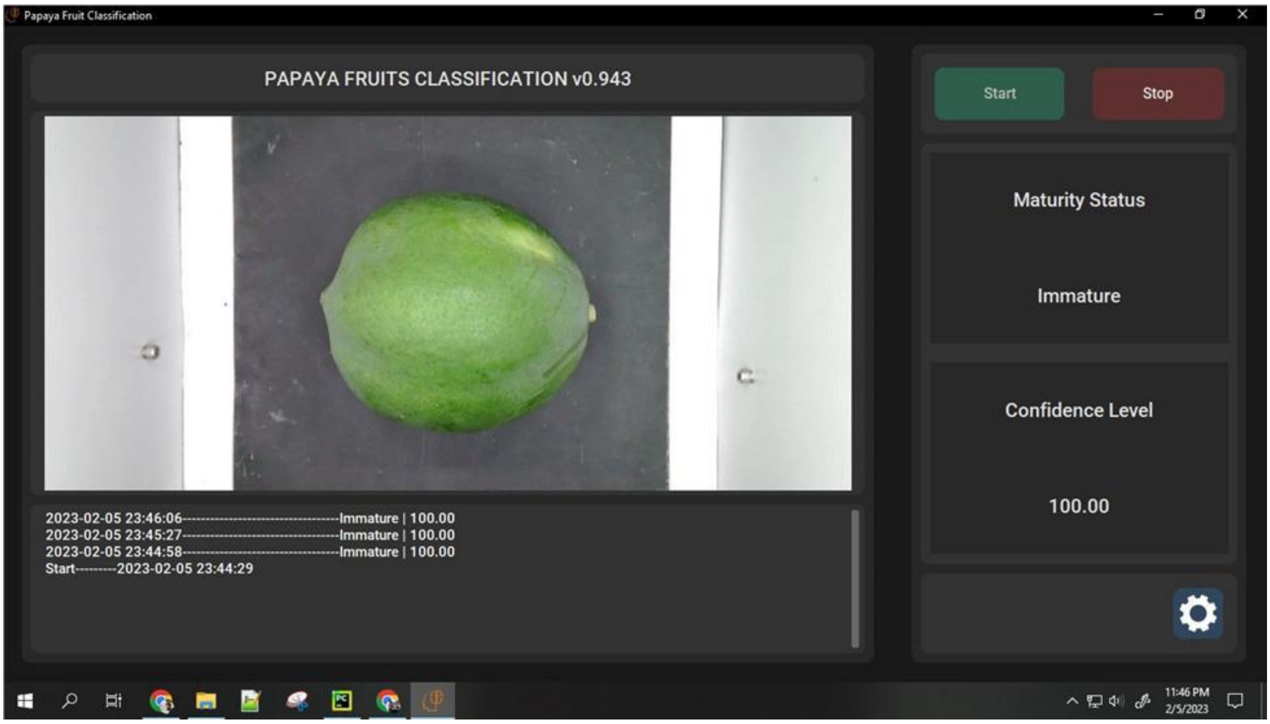

Fig. 5. Graphical user interface (GUI).

III. Results and Discussion

This section discusses different results obtained by training different CNN models. Since the transfer learning approach was used for this project, four (04) different pre-trained models: EfficientNetV2B1, MobileNetV3, ResNetRS50, and VGG19 were considered. An MSI laptop with the following specifications: an i7 9th generation processor, 2.60 GHz, 8GB of RAM, and an NVIDIA GTX 1650 4GB GDDR5 graphic card was used to train the models. The same dataset was used to train all four (04) models, and this data set was divided into three (03) subsections: training, validation, and testing. Tab. 1 illustrates the image distribution among the subsections.

TABLE I. Collection of the Images

	Number of Images		
	Immature	***Mature***	***Over-mature***
Training	1367	1054	1109
Validation	43	26	35
Testing	25	24	24

In the training, the process can measure the time taken for epoch, loss, and accuracy. Even if we could measure loss and accuracy using only the training dataset it could be misleading due to the over-fitting issues. The best solution for this over-fitting issue is to use a validation data set.

TABLE II. Summary of the Models Trained

Model	Number of Epoch	Training Accuracy (%)	Training Loss (%)	Validation Accuracy (%)	Validation loss (%)	Average Time per Epoch (s)
EfficientNetV2B1	10	99.38	1.74	100	0.31	102.7
MobileNetV3	10	99.83	0.67	100	0.0066	53.8
ResNetRS50	10	98.70	4.64	100	0.54	291.7
VGG19	30	100	0.0000027	85.58	151.37	6.1

In this project, a completely new set of images was used as the validation data set. During the validation procedure, the model generates a prediction on these new images and categorize them. Subsequently, these predictions are compared to the actual categories to obtain measurements. These measures manifest as val_loss and val_accuracy in the training process, serving as reliable indicators of precision. Also, these readings facilitate comparison with loss and accuracy values to identify the over-fitting during the training process. The testing data set can be used to get a confusion matrix indicating the number of true positives and the number of false positives produced by the model. The summary of the results of the four (04) models is shown in Table II.

Since the accuracy calculated using the validation set tends to be more reliable than other parameters, it can be deemed as the true accuracy of the model. However, to have a more comprehensive understanding, the parameters, including the confusion matrix, training accuracy, and validation accuracy can be considered. According to the results above, the best performance was exhibited by "MobileNetV3". It was able to reach 100% validation accuracy within 10 epochs, and the loss was 0.006%. Not only the validation accuracy but also the training accuracy reached 99.83% at a minimum loss of 0.67%. For "MobileNetV3", the validation accuracy and loss were close to training accuracy and loss, as shown in Tab. 2. Further, the average time taken for an epoch was comparatively less (53.8 s) than other models that reached high accuracy.

IV. Conclusion

In this project, an automated system comprised of a conveyor system was successfully developed to classify the maturity status of papaya fruits. In implementing the project, four (04) pre-trained deep-learning models: EfficientNetV2B1, MobileNetV3, ResNetRS50, and VGG19 were considered. Among the models trained, "MobileNetV3" showed outstanding performance by achieving 100% accuracy within just 10 epochs while maintaining an extremely low loss of only 0.006%. According to the results obtained, transfer learning is a viable approach for the classification of papaya fruits based on their maturity status. The study also highlighted several challenges that need to be addressed to improve the performance of the model including a large and more diverse dataset, more advanced pre-trained models, and the need to consider other factors, namely lighting conditions and image quality, that may affect the performance of the model. Additionally, it would be beneficial to classify papaya fruits into more than three (03) maturity statuses to ensure better product quality and to train the system to classify more varieties of fruits.

Acknowledgment

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