Engineering and Applied Science Research 2022;49(4):521-530 Research Article

EASR

Engineering and Applied Science Research

https://www.tci-thaijo.org/index.php/easr/index

Published by the Faculty of Engineering, Khon Kaen University, Thailand

DIPDEEP: Classification for Thai dragon fruit

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Received 5 December 2021
Revised 5 February 2022
Accepted 25 February 2022

Abstract

Thai dragon fruit is an interesting fruit with beautiful colors and high nutritional value, which can be used for food and pharmaceutical. In Thailand, there are 7 species of dragon fruits. Its skin can be divided into red or yellow groups, but inside can be divided into white, red or pink groups. If farmers know the species of dragon fruits, they can export fruits at a good price. Most people are unable to distinguish species of the dragon fruits. This paper is focus on classifying species of dragon fruits from images using digital image processing and deep learning called DIPDEEP. The DIPDEEP method has three steps; color space transformation, calculation ratio of the yellow and red color, classification using the deep learning method. First, the Thai dragon fruit images were classified into yellow (1 species) out from red (6 species). The Thai red dragon fruit was resized into 100x100 pixel resolutions in the pre-processing step only 6 species. Then, the red class was sent to classify again using the deep learning method. The experiments were processed in a dataset with 9,754 dragon fruit images on a black background (laboratory), and 10,072 images of dragon fruits at outdoor environment (outdoor). The results showed that accuracy of classification between the red and yellow dragon fruit for laboratory and outdoor datasets was 100% and 95.26%, respectively. The red dragon fruit is classified its species with accuracy 98.80%. The DIPDEEP has the smallest file size, and can save workload time because of separating yellow skin out at first step.

Keywords: Dragon fruit, Classification, Digital image processing, Deep learning

1. Introduction

A dragon fruit is a fruit of the cactus family, having high nutritional value utilized [1]. In Thailand, dragon fruits are traded in both domestic and international markets. During the epidemic situation of COVID-19, trading of dragon fruits and its branches continues unaffected. They can trade through social media.

National Bureau of Agricultural Commodity and Food Standards, the Ministry of Agriculture and Cooperatives of Thailand, has classified the dragon fruits into 3 main groups, which have differences in its peel color and the fruit pulp inner color; namely Group 1 for red skin with white flesh (*Hylocereus undatus*), Group 2 for red skin with red flesh (*Hylocereus polyrhizus*) or red skin with pink flesh (*Hylocereus* spp.), and group 3 for yellow or gold skin with white flesh (*Hylocereus* sp. and *Selenicereus* sp.). For export packaging sold with good price, the species of dragon fruit must be identified on the label attached to the front of the package [2]. There are 7 species of Thai dragon fruits, Loei province located at the top of the northeastern region of Thailand can harvest the most dragon fruits [3]. Group 1, there are two species; Jumbo White and Vietnamese White. Group 2, there are four species; Pink, Siam Red, Taiwan Red, and Ruby Red. Group 3, there is only one species called Israel Yellow. Most farmers know only the color of the skin and the pulp. They will sell their harvest to middlemen separated dragon fruits into 3 main groups, but they could not identify its species.

For this reason, the domestic trading price of each type of dragon fruit was determined only according to three main groups. If farmers can classify species of dragon fruits, they will learn how to manage dragon fruits, and how to take care for transportation according to the characteristics of each species that affect the cost and selling price. An academic or an expert farmer required a lot of knowledge and expertise will be able to distinguish species from morphological characteristics. Normally, people are unable to distinguish the species of dragon fruits correctly. Especially the Groups 1 and 2 all of which have the same red skin. This may make a mistake in separating the groups because at the time of purchase cannot see the inside. They may be classified fruit pulp in wrong color, affected the reliability and sale price to consumers or factories. Someone who allergy with specific species could not avoid.

This paper is focus on classifying species of dragon fruits from images using digital image processing and deep learning called DIPDEEP, which is a difference from the classification with specific characteristics such as branches, flowers and fruits [1]. The remainder of this paper presents the relevant researches in section 2, the DIPDEEP algorithm in section 3, the dataset and experimental results in section 4, and the remarkable conclusions in section 5.

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doi: 10.14456/easr.2022.51

2. Theory and literature review

2.1 Color theory

Color in RGB model is a color system formed by mixing three color channels, red, green, and blue. Each channel has a color scale from 0-255. For example, RGB (245, 102, 36) represent an orange color [4]. Color in HSV model approximates the human perception of color. They include Hue (H), Saturation (S), and Value (V). H is a color tone indicated by the angle of the color wheel, which ranges from 0° to 360°.S is the color saturation value. V is the color brightness value. In OpenCV image processing, the H ranges is used in half values. The S and V values range from 0-255. If both values are set to 255, the color tones are clearly displayed. For example, Red Pure has HSV (0, 255, 255), et [5]. Color in LAB model consists of three components: L is the lightness value from black to white, A is the green gradation to red and B is the blue gradation to yellow. In image processing with OpenCV, LAB values are adjusted in the range 0-255 [4].

2.2 Digital image processing

A digital image can be represented by a function of two variables: F(x, y) where x and y are spatial coordinates, each of which is called a pixel. The F value is in range 0-255. Grayscale image consists of one channel and for color images consists of RGB, HSV, or LAB as descript in color theory. Digital Image Processing is the process of taking the color value of each pixel for the intended purposes; image resizing, color converting, data augmentation, or other techniques such as removing the background from an image to reduce noise, etc. [6]

2.3 Feature extraction

Feature extraction selects image features that help identify specific characteristics of all images. There are color, shape, texture, or others expected to be used as criteria for characterizing [6] or searching or sorting images similarly [7, 8]. Of course, the image data may not be the only characteristic that can be characterized. The feature vector, a 1-dimensional array, was used to replace the processing of every pixel of the image data [6]. Characterization generally consists of two parts: feature extraction and similarity measurement [8], both of which must be analyzed and tested to verify validity. The end result may use one or more attributes based on experimental results.

2.4 Deep learning

Deep learning is one of the most popular automated machine learning methods. Provides high predictive performance work as a black box [9] to mimic the work of human neurons by building a neural network with a layer of nonlinear processing overlaid multiple layers [6, 10]. Each layer takes the result of the previous layer as input. The model helps distinguish features automatically. The researcher prepare only information for learning. This makes a lot of convenience for the researchers. There are many researches using Deep learning.

2.5 Literature review

Many previous researches in classification from images have 4 steps: data acquisition, data pre-processing, feature extraction, and then classification [11]. Color, shape, texture, or other features are expected to be used as criteria for finding or sorting similar images [7, 8]. Of course, image data may not contain just one feature that is different. For examples, there are using texture and color properties for image retrieval [12], using apple skin color to assess ripening of apples according to their maturity stage [13], as well as using color features in the classification of cherries by [14].

Deep learning is one of the most popular automated machine learning methods. The highlight of this technique is that it supports classification with fuzzy attributes. The model helps distinguish features automatically. [15] The effectiveness of the deep learning model was tested in detecting white and red grapes by training with 11 architectures, such as ALexnet, Densenet201, Googlenet, InceptionResNetV2, InceptionV3, ResNet18, ResNet50, ResNet101, Squeezenet, VGG16 and VGG19. It was found that the suitable deep learning model for the detection of white grapes was ResNet50 and red grapes was ResNet101. Therefore, a deep learning model to classify these two grapes should use modified ResNet. ln addition, ResNet50 is the winner of ILSVRC 2015 in classification task [16], compared to the performance of VGG16 models that won first and second place in ILSVRC 2014 in localization and classification task respectively [17]. The VGG16 gets less accurate in detecting grapes [15], but it's an interesting model with an 8 times reduction in the number of layers.

The VGG16 model is used in [18] to identify 4 varieties of Taiwan lychee. The results showed that VGG16 was able to identify lychees with an average accuracy of 98.33%. Although the performance of the VGG16 model [18] did not compare with other models, all experimental results confirmed the performance of the deep learning model very well.

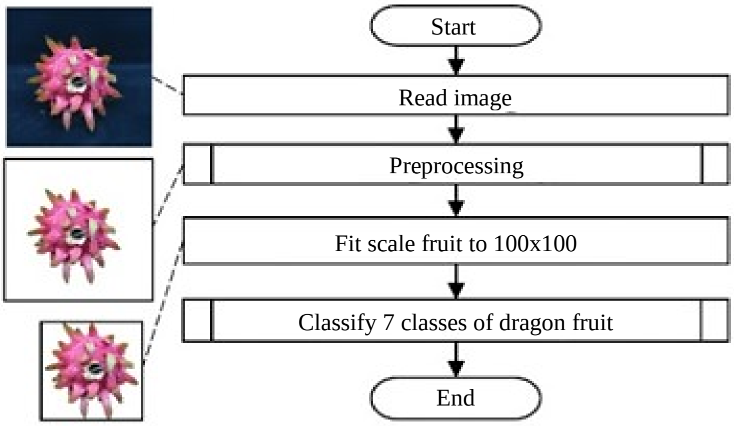
With the evolving technology MobileNetV2 [19], a smaller model, was developed to support the smaller mobile applications, limited computing resources but the performance is still satisfactory. Fruit recognition from images using deep learning presented experimental results for training a CNN to classify many kinds of fruits using Fruits-360 dataset [20]. Food image can be classified by user interactive identify segmentation input boundary and classify using support vector machine [21]. The paper run experiments on Food 101 dataset.

A binary image is used as a criterion to segment cherry fruit from background and then used CNN to classify regular or irregular shaped cherries. The efficiency was compared with the use of KNN, ANN, Fuzzy, and Ensemble Decision Trees (EDT) to classify regular and irregular cherries from the histogram of gradient (HOG) and Local binary pattern (LBP) surface characteristics. The experiment found that CNN was able to correctly identify 99.4% of regular and irregular cherries [22].

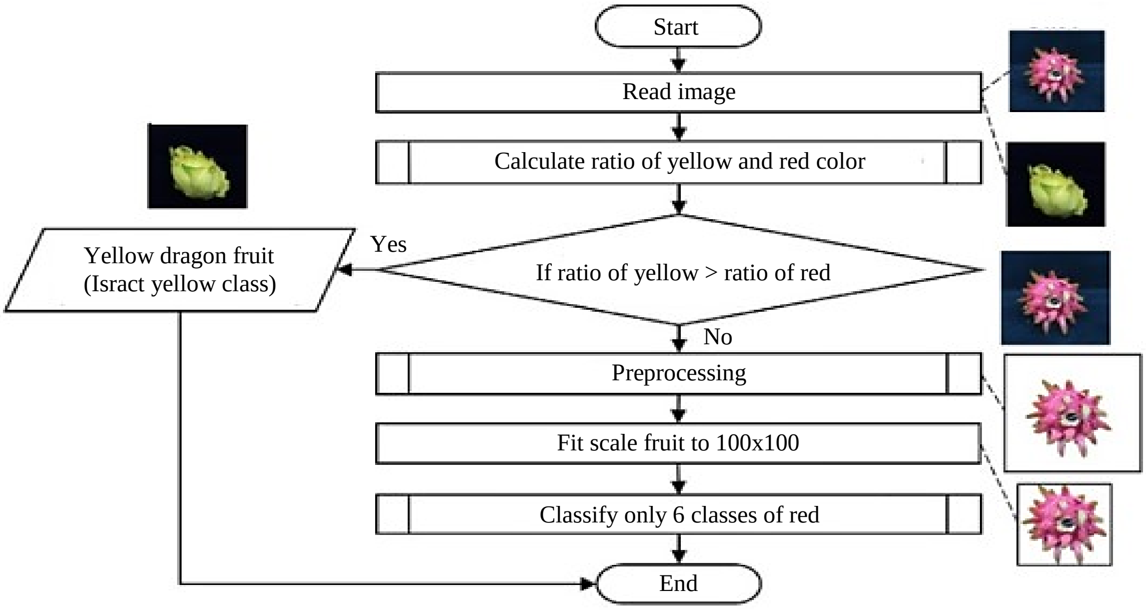
3. The DIPDEEP algorithm

This paper presents algorithms to classify species of dragon fruits automatically called DIPDEEP, consisting of a main program, sub-programs. The program reads a dragon fruit image, and then the result is its species. The DIPDEEP stands for implementation with digital image processing and deep learning. The main program of DIPDEEP (old version) is shown as Figure 1(a). Since the dragon fruit can be distinguished the yellow skin color of the Israel yellow species from the other 6 species with red skin. This paper use the main program of DIPDEEP (new version) as shown in Figure 1(b). This version can reduce classification time.

A subprogram, Calculate Ratio of Yellow and Red color, calculates the ratio of yellow color and the ratio of red color in an image, shown as Figure 2. Then, if the ratio of yellow is greater than the ratio of red, it will be the Israel yellow species and exit. Otherwise, the program will continue a subprogram, Preprocessing, made clear image shown as Figure 3. Then crop the image to a size of 100x100 pixels and come through a subprogram, Classify only 6 Classes of red, using a deep learning model set parameters as shown in Table 1 to distinguish 6 species of red-peel dragon fruit.



(a)



(b)

Figure 1 The main program of DIPDEEP method (a) old version (b) new version.

DIPDEEP method used the HSV color model to separate groups of dragon fruit from its peel color between yellow and red. The peel color morphology of dragon fruit compared to the HSV color wheel revealed that the yellow-peel fruit had H value close to 23°-37°, the entire yellow tone of the color wheel. Red-peel dragon fruit has H value close to 0°-23° and 151°-179°, the red and magenta tones of the color wheel respectively. Therefore, the DIPDEEP method used H values to classify dragon fruit groups from it peel color as shown in Figure 2 with OpenCV processing. The yellow ratio and the red ratio were returned to the main program.

In digital image processing, the RGB channel can be spited from 3 channels into a single channel. This is easier to process than three-channel simultaneous processing. From Figure 3, DIPDEEP method uses only R channel to calculate the mean threshold value, used Equation (1), as a criterion for conversion color image into binary image, preprocessing to reduce noise in an image and can extract object from background pixels.

$$mean\ threshold = \frac{\sum R}{N} \tag{1}$$

Where R is the R value of RGB model in each pixel, and N is the total number of pixels. When the value of mean threshold is returned, each pixel is compare its R value with the value of mean threshold. If the R value is greater than, this pixel will be set to white color as an object. Otherwise, this pixel will be set to black color as a background. There is used morphology function opening to modify the object boundary smoother and used the Fill Hole from the OpenCV program to fill any hole in the object. Then background is switched to white color, and the object area is switched to the same area of the origin image. The image obtained in this step is cropped to a specific proportion of the dragon fruit to 100x100 pixels and returned to the main program used as input to the next step, the deep learning model. After the main program get clear object from its background, then call a subprogram, Classify only 6 Classes of red. The deep learning model to distinguish 6 species of red-peel dragon fruit was set parameters as shown in Table 1, giving the optimized efficiency model.

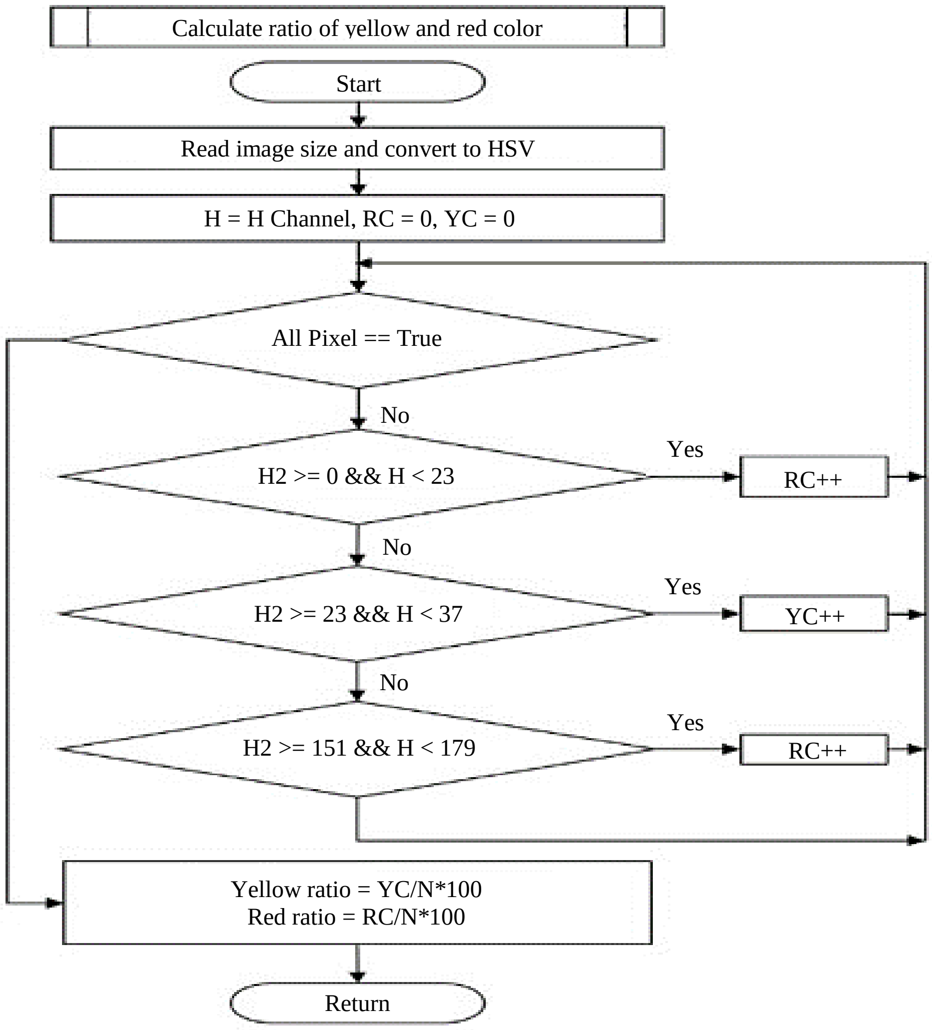


Figure 2 Calculate ratio of yellow and red color subprogram.

Table 1 The structure of the convolution neural network used in the DIPDEEP method.

Layer	Size	Type	Output
Input	100x100x3		
Layer1	96x96x16	Convolution 2D (5x5) + ReLU	16
Layer2	48x48x16	MaxPooling (2x2)	-
Layer3	44x44x32	Convolution 2D (5x5) + ReLU	32
Layer4	22x22x32	MaxPooling (2x2)	-
Layer5	18x18x64	Convolution 2D (5x5) + ReLU	64
Layer6	9x9x64	MaxPooling (2x2)	-
Layer7	5x5x128	Convolution 2D (5x5) + ReLU	128
Layer8	2x2x128	MaxPooling (2x2)	-
Layer9	1x1x512	Flatten	512
Layer10	1x1x1024	Fully Connected + ReLU	1024
Layer11	1x1x256	Fully Connected + ReLU	256
Output	1x1x6	Fully Connected + Softmax	6

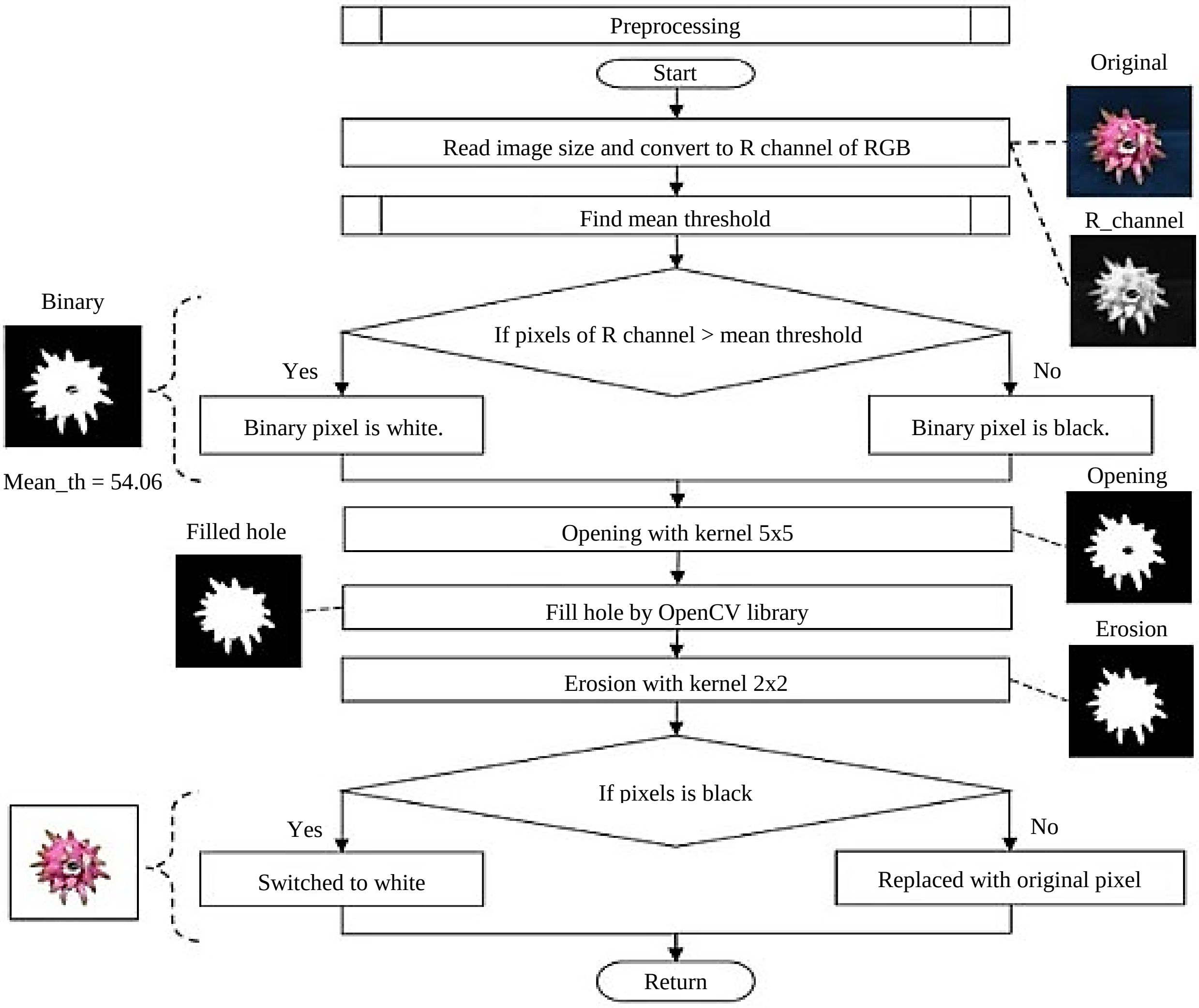


Figure 3 Preprocessing subprogram.

4. Dataset and experiments

Dataset is very important for beginning researches. There are images of dragon fruits from a large image source in Kaggle named Fruit-360 [20] but it does not cover all 7 species of Thai dragon fruits. This research have to create a new dataset, 7 species of Thai dragon fruits are collected between August-October 2020 from 7 plantations in Mueang Loei District, Phu Ruea District and Dan Sai District, Loei Province, where gets the highest harvest of dragon fruits [3]. These samples of dragon fruits are less than one week after harvesting.

4.1 Dataset

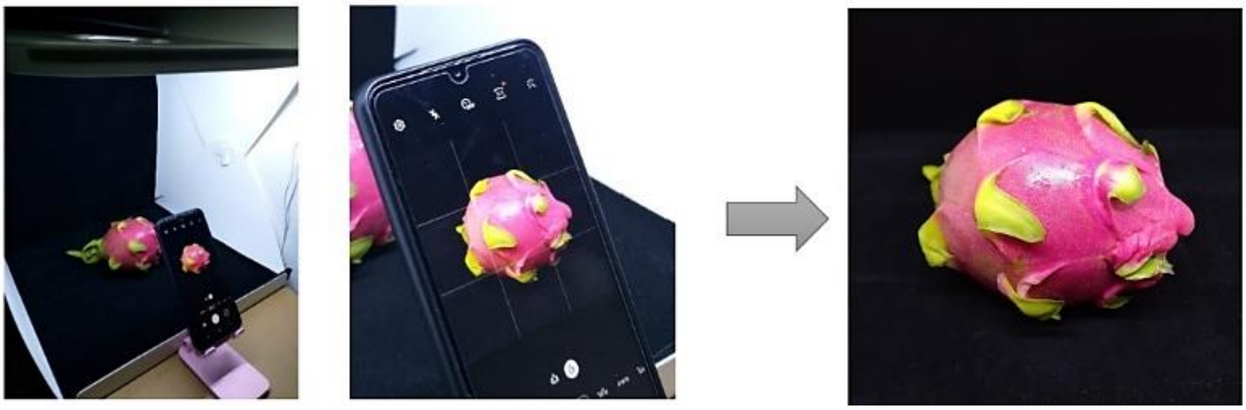
The data set consisted of 9,754 images which were divided into Jumbo White 1,172 images, Vietnamese White 1,190 images, Pink 1,309 images, Siam Red 1,869 images, Taiwan Red 1,184 images, Ruby Red 1,110 images, and Israel Yellow 1,920 images. The dataset used only the mobile phone camera to take images with 1:1 aspect ratio, disables all filters, and the dragon fruit is placed in a portable studio box with size 40x40 cm, floor with black velvet fabric, installed one row of LED lights on the top edge of the box, as shown in Figure 4(a). From Figure 4(b) the object is kept as centered as possible, by using the nine dividing lines of image layout, and try to take images with the object rotated as 0-360 degrees as possible, similar to the images of Fruit-360 [20]. An example image looks like Figure 4(c). Each image contains only one species of a dragon fruit with black background. Each species used samples more than one dragon fruit. After collecting the dataset, botanists and gardeners identify the label again for the accuracy of the species name identification used to validation as a ground truth data.

There are total 10,072 images of dragon fruits in an outdoor environment using a mobile phone camera, with free aspect ratios, such as 3:4, 9:16 in natural sun light as well. The results of images have a more complex background, with different image sizes as shown in Figure 5. If innovations are developed in the future that farmers or tourists can use the camera of a mobile phone to easily detect the species of dragon fruit without using a ruler or a proficient tool. It will be great challenge for future researches.

4.2 Experiments for the preprocessing subprogram

The DIPDEEP ever testing RGB, HSV, and LAB to determine the channel of the image converted to binary image can be used to separate the background image from the dragon fruit effectively. From the experimental results, the R Channel of the RGB model gave the best results as shown on Figure 6.

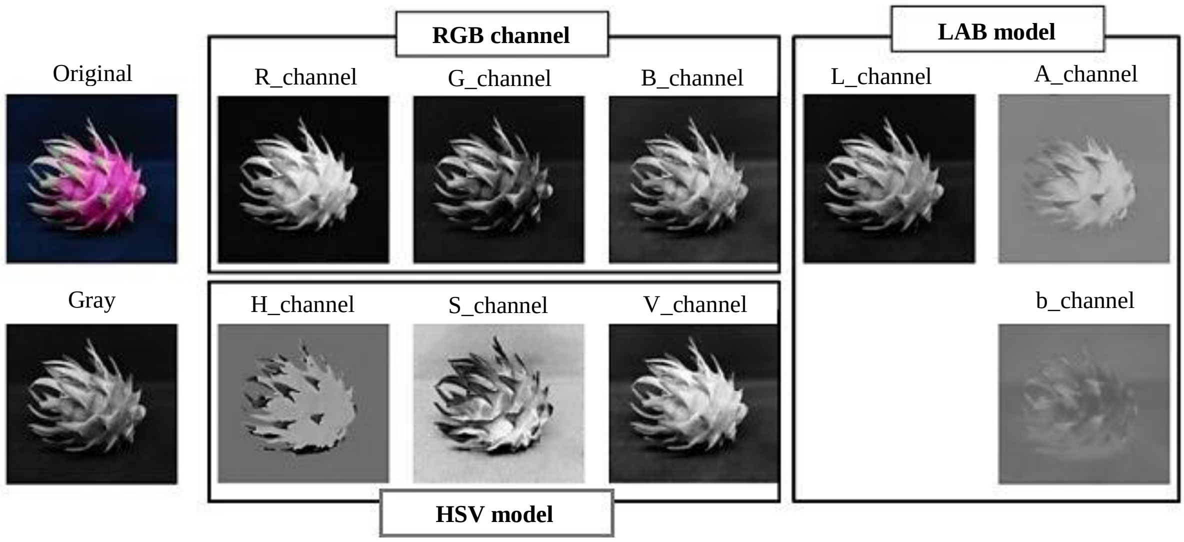
From Figure 7, an example image is presented results for each process step to extract an object from its background following a subprogram in Figure 3, beginning with an original image, follow with the binary result after segmenting with the mean threshold, the result after processed with function Opening, the result after Fill Hole, the result after running function Erosion, and then the result of an image after remove background. Then crop the result image, with the centered object, to fit with 100x100 pixels similar to [20] as shown on Figure 8. From Figure 9, example images represent results after done with the Preprocessing subprogram. There are 7 species of dragon fruits, which is ordered from left to right are Pink, Siam Red, Taiwan Red, Ruby Red, Jumbo White, Vietnamese White and Israel Yellow species, respectively. From Figure 10, each column displays, ordered from top to bottom, a dragon fruit image, an image showing pixels of yellow color position and its yellow ratio value, an image showing pixels of red position and its red ratio value of H channel in the HSV model. For each column in Figure 10, any dragon fruits with red skin have their red ratio value more than their yellow ratio. The Israel Yellow, the last two columns on the right hand side, has its yellow ratio value more than its red ratio value. Therefore the yellow ratio value and the red ratio value can be used to identify skin color of dragon fruits.



(a) (b) (c)

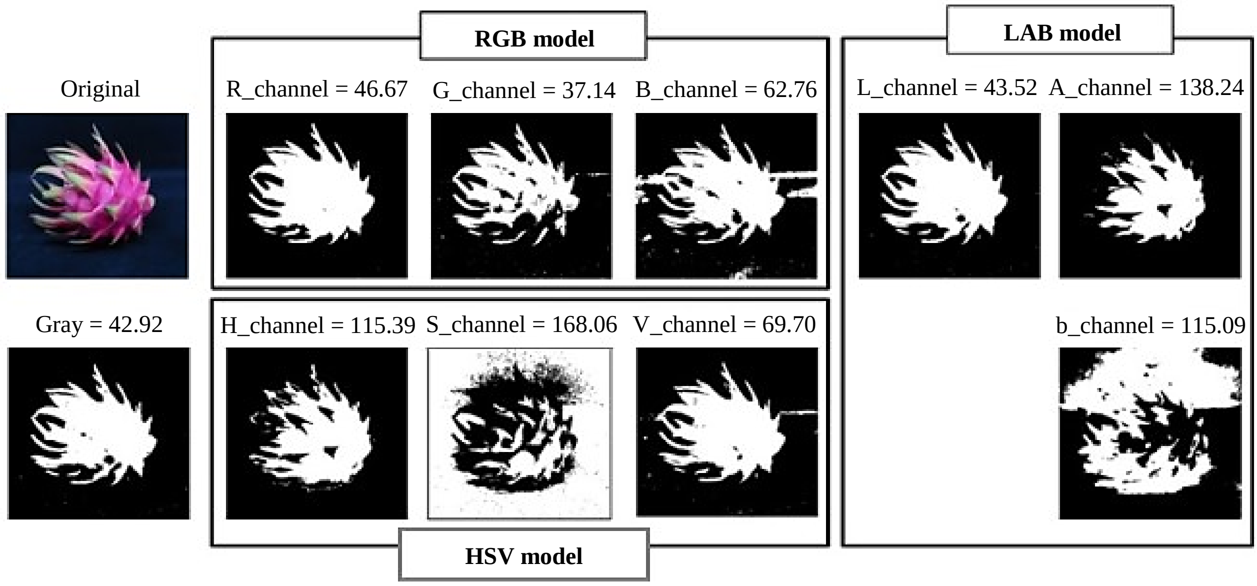
Figure 4 (a) Show the device to collect the data (b) imaging techniques (c) a sample of data.

Figure 5 Samples of a dragon fruit image in an outdoor environment.



(a) Show result of converting 3 channels to 1 channel for either RGB, HSV, or LAB model.

Figure 6 (a) An image in either original, gray, RGB, HSV, or LAB model, (b) binary image.



(b) The results respectively in (a) after convert all channel to binary by using mean threshold.

Figure 6 (continued) (a) An image in either original, gray, RGB, HSV, or LAB model, (b) binary image.

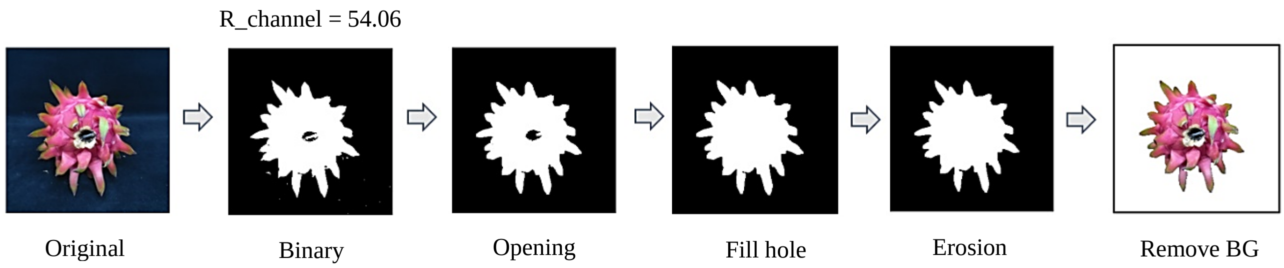


Figure 7 Illustration of each step to extract object from its background.

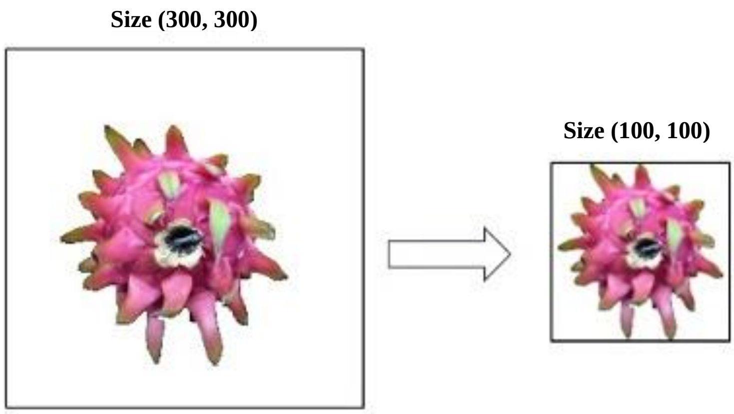


Figure 8 An example of cropped the object to fit scale 100x100 pixels

Figure 9 Results after done with the preprocessing subprogram.

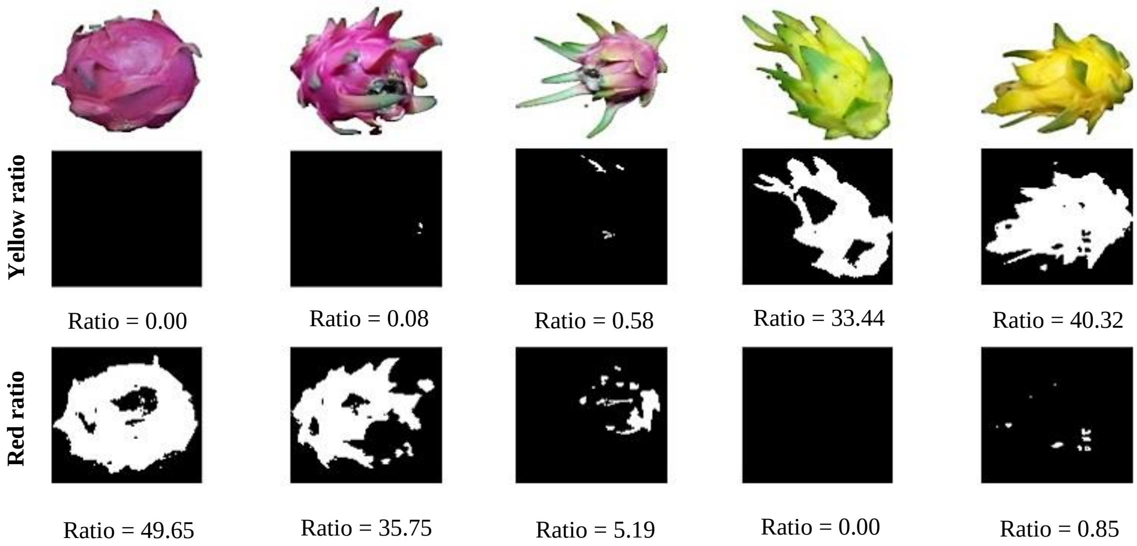


Figure 10 Results for each column, original image, its yellow ratio value, and red ratio value.

4.3 Experimental results

Before doing the experiments, images of 7 species of dragon fruit were randomly selected 1,000 images per species, divided into 800, 100, and 100 images for the Training Set, the Validate Set, and the Test Set, respectively. Using the 10-Folds Validation technique. All of the selected images were processed with main program. Experimental results after finished the Preprocessing subprogram as shown in section 4.2 are used as input data for running the deep learning in the subprogram named Classify only 6 Classes of red, in the main program (new version), and Classify 7 Classes, in the main program (old version). A 100x100 pixel image is used to process with a deep learning model Structured as Table 1.

From Table 1, Output Layer was set the output equal to the number of classes. Therefore, the output node is equal to 6 nodes for DIPDEEP new version, and 7 nodes for DIPDEEP old version. The rest of the parameters that are not specified using all Keras default values. The model uses the Adam algorithm optimizer, the learning rate is 0.001 in the Training process, by assigning Batch Size equal to 100 and assigning multiple Epochs namely 10, 20, 30, 40, 50, 100, 300, 400 and 500 epochs to test which Epoch will be the best and get the highest accuracy. The results of classifying of 7 Classes are comparing between the Fruit recognition method [20] and The DIPDEEP (old version) shown on Table 2. From the results, it was found that Epoch equal to 100 was the most suitable because it could provide the highest accuracy of 98.20%.

From Table 3, results showed that DIPDEEP method can classify between Yellow and Red skin species correctly with accuracy 100%. All of experiments were explained only using Laboratory Dataset. From Table 4, results showed any numbers of samples in from both Laboratory Dataset and Outdoor Dataset using DIPDEEP method. In this experiment, Red skin and Yellow skin can be classified correctly with accuracy 100 % in Laboratory Dataset. But Outdoor Dataset can be classified correctly with accuracy 95.26%, lesser than results of Laboratory Dataset. Because it has more complex background. The accuracy to separate species of the Outdoor dataset is not stable because of its accuracy was less than 100%. Therefore, the Outdoor dataset did not process other steps yet.

Table 2 Percentage accuracy of results between the fruit recognition method and DIPDEEP

epochs	Mean (SD.)					
	Fruit recognition method [20]			**DIPDEEP Method**		
	Train	**Valid**	**Test**	**Train**	**Valid**	**Test**
10	97.41(1.00)	95.09(1.37)	94.49(1.03)	97.60(0.72)	95.59(0.83)	94.06(1.21)
20	99.64(0.59)	97.11(1.10)	96.46(1.05)	99.83(0.50)	97.81(0.75)	96.99(0.88)
30	100(0.00)	98.20(0.55)	97.70(0.47)	100(0.00)	98.74(0.52)	98.00(0.39)
40	100(0.00)	98.50(0.38)	97.66(0.36)	100(0.00)	98.71(0.46)	97.96(0.38)
50	100(0.00)	98.13(0.44)	97.49(0.60)	100(0.00)	98.61(0.55)	98.11(0.32)
100	100(0.00)	98.36(0.46)	97.56(0.89)	100(0.00)	98.74(0.27)	98.20(0.44)
300	100(0.00)	98.37(0.43)	97.60(0.84)	100(0.00)	98.71(0.56)	97.99(0.72)
400	100(0.00)	98.13(0.79)	97.39(0.60)	100(0.00)	98.67(0.53)	97.67(0.88)
500	97.65(5.65)	93.09(6.35)	77.33(21.49)	100(0.00)	96.21(2.27)	88.61(9.63)

Table 3 Percentage accuracy of classification results between yellow and red

	Train		**Valid**		**Test**	
	Samples	**Hue range**	**Samples**	**Accuracy**	**Samples**	**Accuracy**
Yellow (1 species)	800	23-37	100	100%	100	100%
Red (6 species)	800	0-23 and 151-179	100	100%	100	100%

From Figure 1(b) and Table 3, the results showed that the H channel of HSV color model can classify the Israel Yellow species from the other 6 species with 100% accuracy. And the deep learning in DIPDEEP new version can classify 6 species of red-skin dragon fruits with accuracy 98.80% as showed on Table 5. Table 5 reported the comparison for accuracy of classification methods, such as ResNet50 [16], VGG16 [17], MoBileNetV2 [19], and DIPDEEP. The results showed that ResNet50 and MoBileNetV2 for training set cannot get accuracy 100%, and cannot use to compare results. The VGG16 get accuracy 98.70 % and DIPDEEP get accuracy 98.80%. Therefore the DIPDEEP model is more suitable for classifying the 6 species of Thai dragon fruits. The DIPDEEP is fine-tune the CNN architecture, which is similar to the VGG16 in that the number of layers is reduced from 16 to 13, and the filter size is reduced to 16, 32, 64, and 128, but the kernel size of the convolution layer is increased from 3x3 to 5x5. Importantly, the file sizes of DIPDEEP, ResNet50, VGG16 and MobileNetV2 are 12.2 MB, 270.7 MB, 542 MB and 26.5 MB, respectively. The DIPDEEP method is the smallest size. The confusion matrix with 100 epochs for 6 classes shows as shown on Figure 11. Examples of the misclassified images were shown on Figure 12. Taiwan Red is very similar with Ruby Red. Therefore these species have the less average of accuracy rate than other.

Table 4 Classification results between red and yellow with 2 different datasets

Species	Laboratory dataset		Outdoor dataset	
	Samples	Accuracy	Samples	Accuracy
Pink	1,309	100.00%	1,058	100.00%
Siam Red	1,869	100.00%	974	97.84%
Taiwan Red	1,184	100.00%	1,111	86.41%
Ruby Red	1,110	100.00%	903	98.00%
Jumbo White	1,172	100.00%	1,603	92.33%
Vietnamese White	1,190	100.00%	2,925	92.44%
Israel Yellow	1,920	100.00%	1,498	99.80%
	Mean	**100.00%**	**Mean**	**95.26%**

Table 5 Comparison for accuracy of classification methods (for 6 species of red skin).

	Mean (SD.)			
	ResNet50[16]	**VGG16[17]**	**MoBileNetV2[19]**	**DIPDEEP**
Train	99.73 (0.85)	100.00 (0.00)	86.56 (11.86)	100.00 (0.00)
Valid	99.13 (1.64)	98.80 (0.32)	85.43 (12.36)	98.45 (0.62)
Test	99.13 (1.65)	98.70 (0.41)	86.05 (11.85)	**98.80 (0.48)**

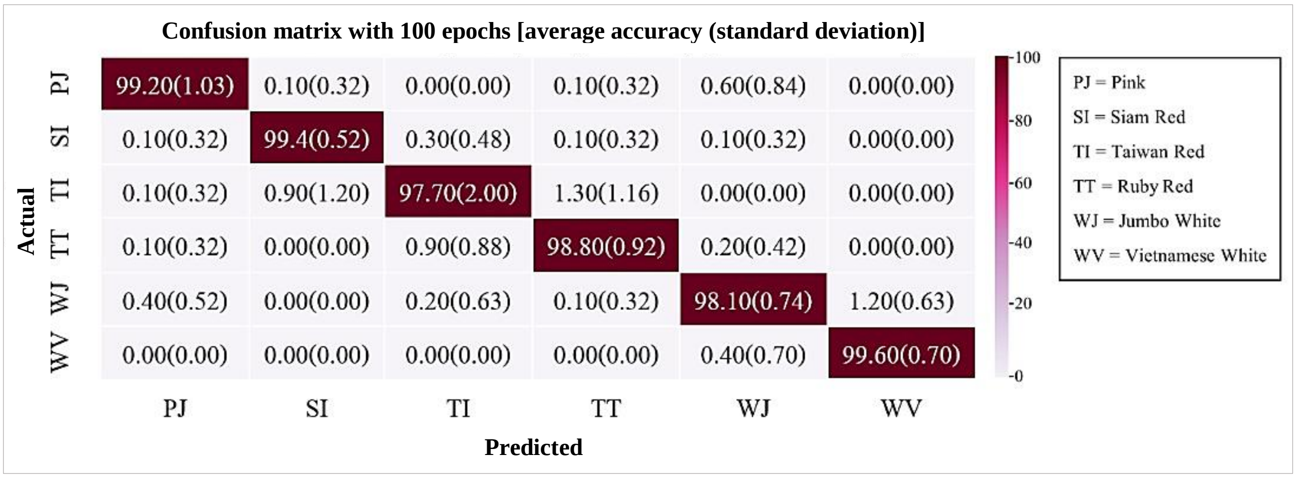


Figure 11 A confusion matrix with 100 epochs for classification 6 species.

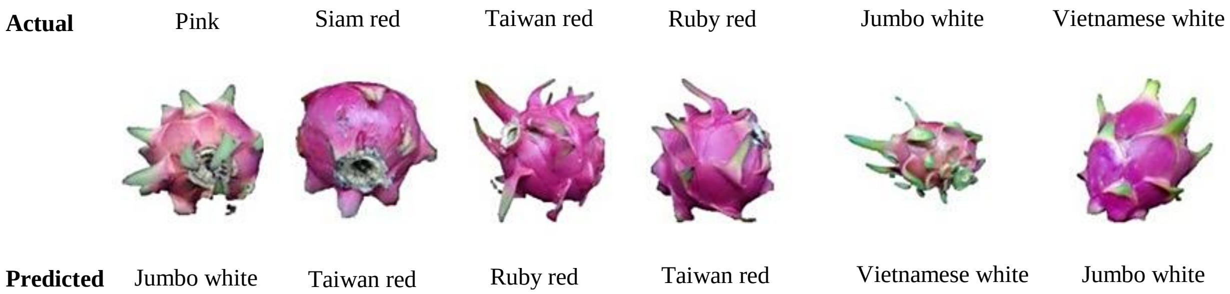


Figure 12 Examples of the misclassified images.

5. Remarkable conclusions

In DIPDEEP method, the color characteristics H of the HSV color model were used to distinguish dragon fruit from its peel color between yellow and red. When a yellow-peel dragon fruit is detected, the results of the cultivar classification can be concluded immediately because of only one species in yellow color. This reduces the work of the computer as well. In the pre-processing step of DIPDEEP, used the color characteristics R of the RGB color model to reduce noise in the image and can help to detect dragon fruit from the background. The DIPDEEP method modified deep learning to classify 6 species of Thai red dragon fruit. This DIPDEEP method is an automatic method with smallest file size, compared with ResNet50, VGG16 and MobileNetV2, and save time because it can classify the Israel Yellow species out with accuracy 100% before doing classify the other 6 species, with the accuracy value 98.80%. This method can help farmers, consumers, and factories to classify species of Thai dragon fruit, and help famers selling their products in higher price or help someone who is allergy with specific species can avoid it correctly. All experiment results used only the Laboratory dataset. Since from Table 4, the Outdoor dataset was used to classify between the Israel Yellow with the other 6 different species which accuracy was less than 100%, and did not process other steps in DIPDEEP yet. Therefore, the Outdoor dataset needs to be studied more for the future work.

6. References

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