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Papaya Fruit Maturity Estimation Using Wavelet and ConvNET

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ABSTRACT

The papaya (Carica papaya L.) is a tropical fruit with high commercial value due to its superior nutritional and therapeutic properties. Papayas must be packaged in the fruit industry according to their degree of ripeness. Physically grading papaya fruit using human vision is time-consuming and destructive. A brand-new, non-destructive classification system for papaya fruit development stages is being offered as a result of this study. The project proposes to investigate three classification models: one deep learning method, the DWT approach, and a hybrid approach. A total of 300 papaya fruit sample photos were used in the experiment, 100 of which corresponded to each fruit's three ripeness stages: mid-ripen, ripen, and un-ripen. The maturity level of papaya is estimated using a hybrid network, i.e., the combination of high-level features and an SVM classifier. The high-level features are the integration of deep Features of VGG16 and coefficients of DWT. The accuracy and AUC of the proposed hybrid model are 98% and 100%, respectively.

1. INTRODUCTION

Papayas, often known as papaws or pawpaws, are tropical fruit belonging to the family Carica. They are a popular fruit because of their sweet flavor, vibrant color, and the many health advantages they provide. Previously an uncommon and exotic fruit, papayas are now widely available throughout most of the year. Papaya may lower your risk of diabetes, cancer, and heart disease. Additionally, it might help you better regulate your blood sugar if you have diabetes, reduce your blood pressure, and hasten the healing of wounds. Papayas are soft, fleshy fruits that can be used in a variety of dishes [1-4]. When taken off the tree at the right stage of maturity, papayas are said to be able to continue to ripen. Earlier, a damaging procedure was used to assess the quality of papaya. This method's consistency in sorting and time requirements while handling large-scale processing may result in post-harvest losses. Researchers have created several non-destructive approaches for evaluating quality due to advancements in instrumentation technology. Non-destructive techniques are quicker and more effective than conventional methods [5]. To address the problem, non-destructive techniques must be employed to measure the extensive processing of fruits, particularly in the sorting, grading, and marketing lines [6].

Figure 1 illustrates the statistics of papaya production from 2016 to 2020 using data from the Food and Agriculture Organization Corporate Statistical Database [7]. Papaya output is predicted to reach 13,894,705 metric tonnes globally in 2020, an increase of 1.9% from the 13,641,294 tonnes produced in 2019. Again, India was the biggest producer, with more than 43% of global production.

This paper proposes a hybrid network to classify the papaya fruits according to their maturity level comprising high-level feature extraction techniques and a machine learning classifier. Here, the high-level features are extracted using DWT, and those obtained features are combined with deep features obtained from VGG16. Then, the combination of high-level fused features is fed to linear SVM for Classification, and the output classified images are obtained. The Papaya images contain hyper spectral data. Therefore, it has discriminative spatial and spectral characteristics. Multiple classifiers are available in the literature to classify hyper spectral data, such as SVM, ANN, Sparse representation methods, and Random Forest methods.

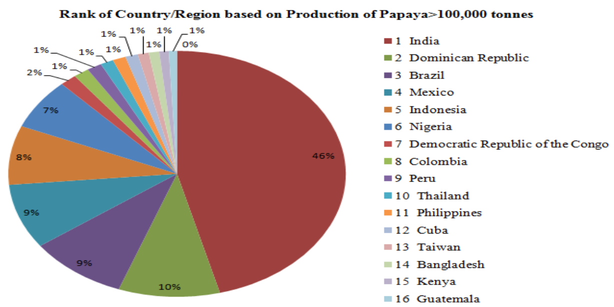


Figure 1. Worldwide of papaya production statistics from 2016 to 2020

DWT represents the images at more than one resolution by discrete sampling, which is very helpful for analyzing the images. Moreover, it provides features at various solutions. For example, the spectral information can be obtained using DWT by applying multispectral image data multi-level decomposition. Especially, the variations in the local spectra are detected at different spectral bands of wavelet transformed images. The DWT comprises two main blocks: the Filter Bank (FB) and the Lifting Scheme (LS). The DWT is a truncated wavelet transform that is half the image size at each scale. In the wavelet transform, converting spatial domain inputs to frequency domain is simple. First, the DWT of a signal x is calculated by passing it through a series of filters. Then, the signal is decomposed simultaneously using a low pass filter with impulse response 'g' and a high pass filter with impulse response 'h' [8]. Finally, the outputs giving the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass) are given in the following Eqns. (1) & (2):

$$Y[n] = (X * G)[n] = \sum_{k=-\infty}^{\infty} X[k]G[n-k] \tag{1}$$

$$Y[n] = (X * H)[n] = \sum_{k=-\infty}^{\infty} X[k]H[n-k] \tag{2}$$

Then, the filter outputs are then sub-sampled by two as given in the following Eqns. (3) & (4):

$$Y_{low}[n] = \sum_{k=-\infty}^{\infty} X[k]G[2n-k] \tag{3}$$

$$Y_{high}[n] = \sum_{k=-\infty}^{\infty} X[k]H[2n+1-k] \tag{4}$$

Due to the fact that only 50% of each filter's output characterizes the signal, this decomposition has reduced the time resolution by half. The frequency resolution has increased since each output has a frequency band that is half that of the input. Filter analysis is displayed in Figure 2. There are two ways to use the spatial domain DWT. The results of 1D-DWT are first applied to the horizontal axis before being applied to the vertical axis. The 2D-DWT produces the four parts LL, LH, HL, and HH.

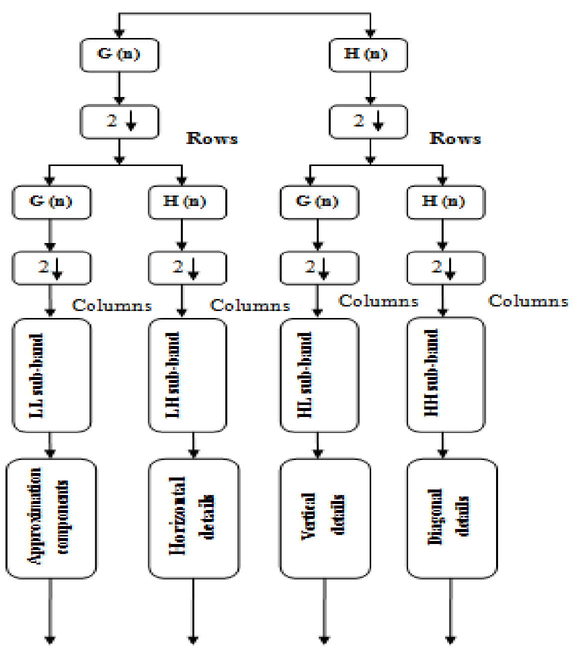


Figure 2. Discrete wavelet transforms

The two-dimensional DWT affects all of an image's rows and columns. For example, the input image size at level L+1 will be 2k/2x2k/2 if the input image is 2kx2k pixels in size. Wavelets across an image employ a variety of decomposition algorithms. The DWT is used to break down the input image into four sub-images. Sub-bands are the names given to these smaller images. The coarse level sub-image is represented by the LL sub-band, while the diagonal, vertical, and horizontal components are represented by the HH, LH, and HL sub-bands. The input image is finally split into four major components, as shown in Figure 2. For multi-resolution analysis, LL frequency and low pass components create a high-level 2D-DWT.

Machine learning algorithms can perform tasks such as categorizing and predicting a wide variety of fruit image types. Learning algorithms are described by Deep Learning (DL) algorithms, which are a subfield of machine learning. These algorithms mimic how the human brain learns using ANNs. It makes it possible for machines to process high-dimensional data such as images, videos, and multidimensional anatomical images, among other data types. Above all else, it is obvious that AI has added a new dimension to the field of agriculture, and it is increasingly becoming available as a substitute for conventional recognisation procedures.

The VGG16 is a CNN comprised of 16 layers. In these sixteen layers, 5 Layers are CNNs followed by Max pooling layers and 2 Layers are fully connected hidden layers, and one layer is a fully connected output layer. The activation function used in VGG16 is ReLU. Multiple GPUs can be used to train the VGG16. Conventionally, CNN's “pool” outputs of neighboring groups of neurons with no overlapping. VGG16 had 138 million parameters which is a major problem in over fitting, and this can be avoided in two methods 1. Data Augmentation and 2. Dropout. In this paper, data augmentation is taken. There are many challenges in using AI technologies in the fruit industry sector. Hence, there is more scope for research in this area. The main contribution of this paper is the utilization and combination of high-level features obtained from DWT & VGG16 to enhance the classification accuracy of SVM for the Classification of Papaya images.

2. RELATED WORK

Fruits' maturity status can gauge how good they are to eat and how long they should be stored before consumption [8]. However, it takes a long time and causes damage to determine these properties with human operators. Therefore, in this application space, quick, clever, and non-destructive approaches are needed [9]. According to their level of development, the papaya fruits in this study are divided into three categories.

The work of numerous researchers in predicting the maturity status of various fruits has been published. Therefore, a fuzzy model [10] is recommended for describing the maturity stage of pineapple fruit. Here, the characteristics of the hue channel and CIE Lab* are displayed. The fuzzy model was optimized using particle swarm optimization, which has a 93.11% accuracy rate.

Two automated systems, the mean color intensity algorithm and the area feature algorithm, are used to analyze the three-level maturity classification of banana fruit [11]. Geometrical features and the GLCM feature are both used for categorization. 120 banana fruit photos, including 40 young, 40 ripe, and 40 over-mature fruits, are used to test the algorithms. According to the investigation, the average color and size of the banana fruit are what most influence classification. With 99.1% accuracy, the mean color intensity algorithm correctly identified the three banana maturity phases. Additionally, the area feature algorithm's limitation was its inability to distinguish between mature and over-matures banana fruits. “The mango fruits were divided into four categories based on their maturity degree using a fruit sorting system. The video was recorded using a charge-coupled device (CCD) camera from a conveyer belt containing mangoes. The acquired video signal's frame is then used to extract 27 features. For classification purposes, recursive feature removal with SVM was also used. 16,400 photos are used to evaluate the system, with a 96% accuracy rate [12].” “The oil palm fruits in the bunch were divided into three classes according to their maturity status using a portable four-band sensor device that was developed. The system has four spectral bands ranging from 570 to 870 nm. With 120 different oil palm fruit bunches taken into account, the discriminate with Mahalanobis distance classifier obtained 85% accuracy utilizing spectral characteristics [13].” “Another approach based on multispectral imaging was put out for evaluating strawberry quality attributes and the Classification of strawberry ripeness state. Principal component analysis with back propagation neural network (PCA-BPNN) and the SVM were used. On a dataset of 280 pictures, SVM was reported to have achieved the best accuracy of 100% for ripeness stage categorization [14].” To predict the maturity of the fruit, a non-destructive, non-invasive sensor system is suggested [15]. The technique, which combined the idea of wireless communication with the Ricardian k-factor to anticipate maturity, had a 92.7% accuracy rate. Based on the image processing technique, a maturity classification model for plum fruit [16] is developed. The maturity of plum fruit was assessed using its external qualitative characteristics, including color, texture, and size. Additionally, the research suggests that color features (RGB indices) predominated over texture and size features. According to the experiment's findings, there was a 99.66% correlation between image and chemical analysis. A unique method for predicting the ripening condition of papaya fruits has been proposed by L.F. Pereira et al. (2018) and is based on image processing using random forest (RF). The approach uses 114 samples and 21 handmade traits to categorize the samples into three groups according to their development phases, and it is accurate to 94.7% [17].

Numerous studies on various elements of the fruit industry, including defect detection [17], fruit quality assessment [18], [19], grading [20], and prediction of volume and mass [21], have been published in the past ten years. Once again, a lot of people employ computer vision [22, 23], image processing [24], and machine learning [25] approaches for fruit categorization. In addition, the fruit business makes extensive use of computer vision [26], machine learning [27], and deep learning [28-31]. Numerous studies have been undertaken over the past few years on on-tree detection [32-34], classification [35-38] as well as grading [39-41] of fruits.

3. MATERIALS AND METHODS

Two methods—DWT and Deep learning—are used to categorize the maturity stage of papaya fruit. First, according to the visual characteristics of flesh color, the maturity stage is determined, as shown in Figure 3.

3.1 Data collection

To photograph the fresh papaya fruits, they are taken from the garden and arranged one at a time on white paper. The photos were taken between 10 a.m. and 3 p.m. using a smartphone camera with a 13-megapixel resolution. A Smartphone holding stand is used to keep the distance between the camera and the subject at 35 cm during the picture acquisition process inside. It was made sure that the room had enough natural light and that there was no direct light that could bounce off of the background and cast shadows on it. Additionally, a white background promotes clarity and eliminates visual clutter and obstructions. The dimensions of all the photos have been changed to 227×227×3. According to maturity indices of papaya, the maturity stage: unripen fruit have green skin with no yellow coloration; mid-ripen have green skin with a faint yellow stripe; and ripen have green skin and a well-defined yellow stripe [42]. The visual traits are also shown in Figure 3, dividing the papaya fruits into three classes: immature, mid-ripen, and ripen. Additionally, each sample's transversal and longitudinal cross sections are compared to ensure accuracy. A total of 300 samples are evaluated, with 100 samples from each group.

Fruit type	Maturity Stage	Descriptions	Fruit color	Number of samples
Mid ripen	Partially mature	Green with a distinct yellow stripe		100
Ripen	Mature	Skin is yellow and may or may not have little bright green spots.		100
Un-ripen	Immature	Without a yellow stripe, green skin		100

Figure 3. Papaya fruits with three maturity stages: (a) Immature; (b) Partially Mature; (c) Mature

3.2 Proposed methodology

The proposed classification framework uses spectral coefficients of DWT multi-level decomposition followed by spatial filtering of all LL, LH, HL, and HH coefficients for each level of decomposition. Thus, in our proposed approaches, we perform a spectral DWT multi-level decomposition on the original dataset, which is concatenated with the features obtained from the VGG16. In addition, a Linear SVM machine has been utilized to classify the Papaya images according to their maturity level. The proposed methodology is illustrated in Figure 4.

We suggest a structure in this study that could be used for a three-way categorization challenge. There are three divisions in the structure: (a) Feature Extraction Part - Extracting the most important high-level deep features by fine-tuning the VGG16, (b) Modified Part - Added a concatenation layer, where the high-level features, i.e., coefficients of DWT, are mixed with the deep features of Vgg16, (c) Classification – The SVM performs the classification task by utilization of enhanced high-level features (deep features + DWT coefficients).

3.2.1 Large-scale DWT-based feature extraction

The R, G, and B individual channel-colored images of fruits were separated into up to four layers. Since then, it has been demonstrated that decomposing the image is the most efficient way to uncover the minute details and offer a scale-invariant interpretation of the leaf image. To successfully exclude the crucial distinguishing characteristics of the maturity status for fruit identification, the DWT is employed to explore a number of sub-bands. Images were separated into four unique coefficients, each having a high frequency and a low frequency (in three directions), as illustrated in Figure 4. The DWT [dwt (z)] is produced using the functions [s(z)], also referred to as the scaling function, and [w(z)], which represents the wavelet at decomposition level d.

$$dwt(z) = \sum_x l_d(x) 0.2^{\frac{d}{2}} s(2^d z - x) + \sum_x h_d(x) 0.2^{\frac{d}{2}} w(2^d z - x) \tag{5}$$

In the above equation, dwt (z) is decomposed at the level that provides $l_d(x)$, i.e., coefficients with low frequency, and $h_d(x)$, i.e., coefficients with high frequency, respectively. At various image scales, this decomposition results in varied frequency coefficients. While the low scale high frequency (LSHF) detail coefficients, such as cH (Horizontal), cV (Vertical), and CD (Diagonal), provide minimal information, the approximation coefficient (cA), which has a high scale low frequency (HSLF), provides considerable and high information about the input image. As the CV (Vertical) and cH (Horizontal) sub-bands are respectively sensitive to pose fluctuations and a large amount of the noise effect is attributable to the CD (Diagonal) sub-band, it is possible to separate the characteristics that contribute the most by removing these coefficients from the papaya images.

Since the coefficients (cA, cH, cV, and CD) in this level comprise the major frequency components of the signal required for Classification, 2-level DWT was used in this work. In 2D-DWT, the image is decomposed into high-frequency (details) and low-frequency components (approximation). At every level, four sub-bands are generated. The approximation shows an overall trend of pixel values and the details as the horizontal, vertical, and diagonal components. As 2-level decomposition is carried out, a total of 20 coefficients (16 coefficients of 2nd level and four coefficients 1st level) are generated [40]". The decomposition tree is illustrated in Figure 5. The feature coefficients for each class were calculated using these statistical features. Four rows of feature vectors are created from the obtained parameters. A signal has 20 features per signal. A database containing these feature vectors was developed and used as the input for classifiers.

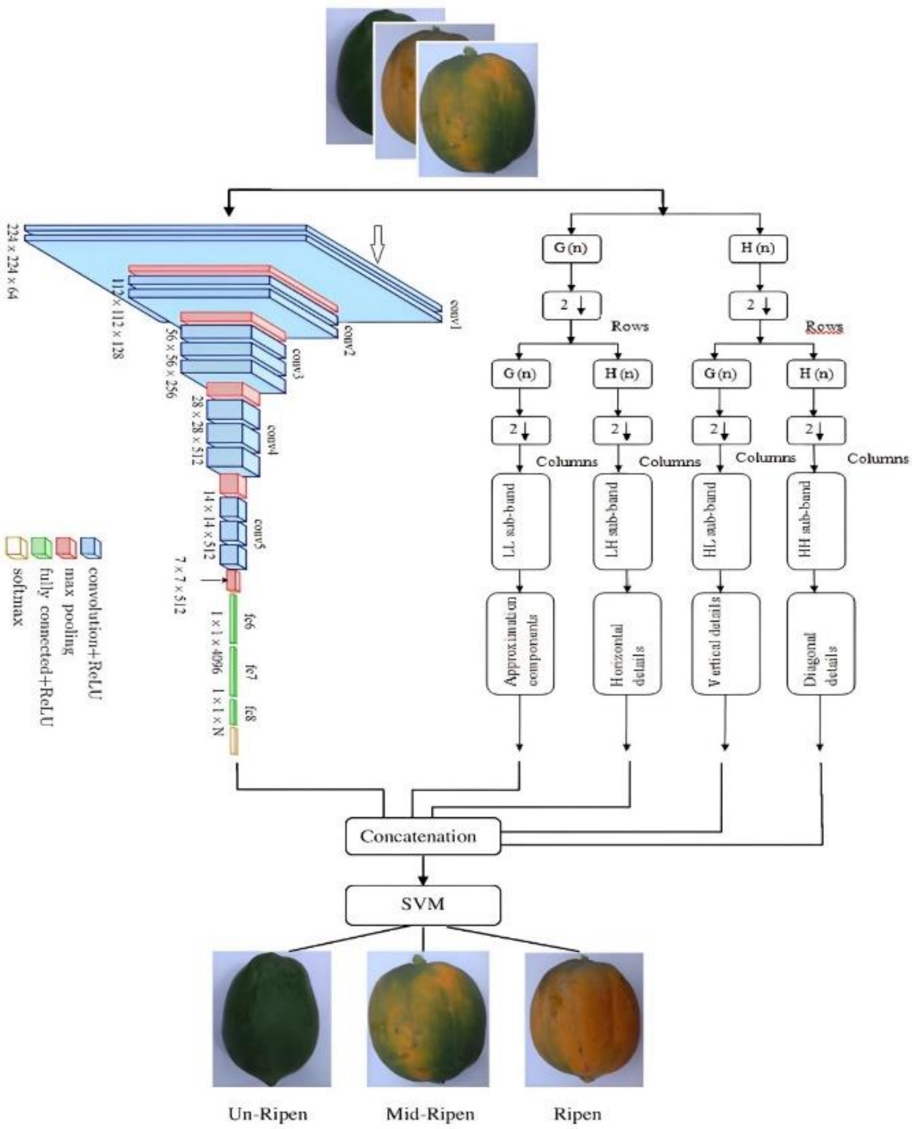


Figure 4. Proposed methodology for classification of Papaya fruits based on the maturity status

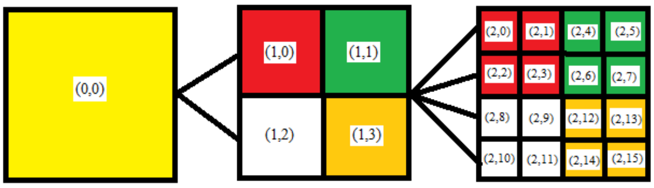


Figure 5. DWT tree decomposition

Here, in the 1st level, the four coefficients such as (1,0), (1,1), (1,2), and (1,3) are generated. Again, in the 2nd level 16 coefficients such as (2,0), (2,1), (2,2), (2,3), (2,4), (2,5), (2,6), (2,7), (2,8), (2,9), (2,10), (2,11), (2,12), (2,13), (2,14) and (2,15) are generated. These 20 coefficients are added to the 1094 number of deep features generated by VGG16. So, 1114 (1094+20) features are fed to the linear SVM classifier.

3.2.2 Machine learning approach

A statistical classifier based on supervised learning, SVM is a widely used regression technique. High-dimensional feature spaces are generally inputted nonlinearly with vectors from supervised learning techniques. By using the principle of construction risk minimization to categorize the papaya into necessary categories based on its maturity status (i.e., un-ripen, mid-ripen, and ripen), the SVM algorithm finds the largest margin in the high-dimensional feature space.

4. RESULT AND DISCUSSION

In this study, we've divided the large-scale robust feature extraction using DWT and deep learning into different categories. Then, the features extracted under VGG16 & DWT are combined parallelly and fed to SVM to classify the papaya fruits. MATLAB 2020a was used to implement the exploration investigation. All the applications were run on a laptop, a Dell Inspiron 15 Core i5 5th Generation with basic NVIDIA GEFORCE. The training parameters such as minibatch size, validation frequency, maximum epoch and the initial learning rate was assigned as 64,30,5 and 0.001, respectively. Also, the stochastic gradient descent with momentum (SGDM) was chosen as a learning method. The activation is in GPU with a minibatch size of 64 and GPU memory have space enough to fit image dataset. The activation output is in the form of the column to fit in linear SVM training. To train the SVM, the function 'fit class error-correcting output codes (fitcecoc)' was used. This function returns full trained multiclass error-correcting output of the model. The function 'fitcecoc' uses K(K-1)/2, binary SVM model, using One-Vs-All coding design. Here, K is a unique class label. Because of error correcting output codes and one-Vs-all coding design of SVM, the performance of classification models was enhanced. The effectiveness of each model is evaluated in terms of *TPR*, *FNR*, *PPV*, and *F*DR are recorded in Table 1. Again, the accuracy and AUC of VGG16, DWT, and VGG16+DWT are recorded in Table 2.

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN}, \qquad \text{PPV}=\frac{TP}{TP+FP}$$

$$\text{TPR}=\frac{TP}{TP+FN}, \qquad \text{FDR}=\frac{FP}{FP+TP} \text{ or } 1\text{-PPV}$$

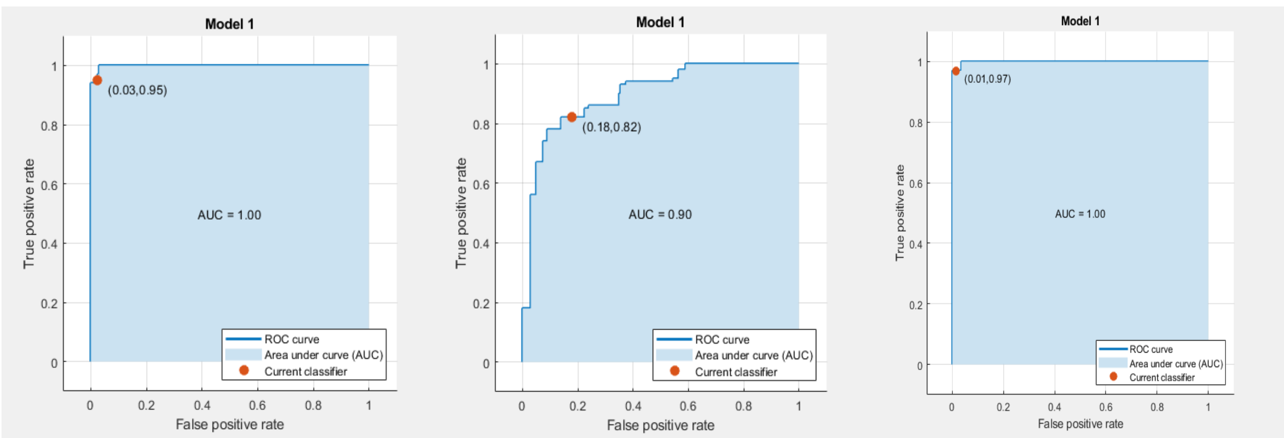
$$\text{FNR}=\frac{FN}{TP+FN} \text{ or } 1\text{-TPR} \qquad \text{AUC=Area under curve}$$

where, TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative, TPR= True Positive Rate, FNR= False Negative Rate, PPV= Positive Predictive Value, and FDR= False Discovery Rate.

Table 1. Comparison of TPR, FNR, PPV & FDR for three different categories of Papaya fruits

	TPR (%)			**FNR (%)**			**PPV (%)**			**FDR (%)**		
Category	**ConvNET (VGG16)**	**Wavelet**	**ConvNET (VGG16)+ Wavelet**	**ConvNET (VGG16)**	**Wavelet**	**ConvNET (VGG16)+ Wavelet**	**ConvNET (VGG16)**	**Wavelet**	**ConvNET (VGG16)+ wavelet**	**ConvNET (VGG16)**	**Wavelet**	**ConvNET (VGG16)+ wavelet**
Mid-ripen	95	82	**97**	5	18	**3**	95	69.5	**97**	5	30.5	**3**
ripen	100	66	**100**	0	34	**0**	100	76.7	**100**	0	23.3	**0**
Un-ripen	95	79	**97**	5	21	**3**	95	82.3	**97**	5	17.7	**3**

**Best results are indicated in bold



(a) (b) (c)

Figure 6. (a) ROC Curve and AUC for ConvNET (VGG16); (b) ROC Curve and AUC for Wavelet; (c) ROC Curve and AUC for ConvNET (VGG16)+Wavelet

Table 2. Comparison of accuracy and AUC for three different categories of Papaya Fruits

Classification Strategy	Accuracy (%)	AUC
ConvNET (VGG16)	96.7	1
Wavelet	75.7	0.90
ConvNET (VGG16) + Wavelet	98	1

The accuracy and AUC of the deep feature of VGG16 with SVM were 96.7% and 1, respectively. Additionally, the accuracy and AUC of the SVM with the Feature Extraction Based on Large Scale DWT were 75.7% and 0.90, respectively. Once more, the parallel feature fusion modification allowed the SVM to reach an accuracy of 98% and an AUC of 1. The ROC curve of three models are illustrated in Figure 6. This investigation showed that adapting the parallel feature fusion technique considerably improves performance. Therefore, the deep feature of VGG16 with Feature Extraction Based on Large Scale DWT and SVM is the best classification model for estimating Papaya fruits into three levels about their maturity stages.

5. CONCLUSION

An automated system for classifying papayas according to their maturity level is crucial for the stock and export markets. Three classification models are all tested in this case: one deep learning method, the DWT method, and a hybrid method. The deep features of VGG16 with SVM and Feature Extraction Based on Large Scale DWT with SVM are examined in the deep learning approach. Based on our extensive experience and fruit identification results, these two classification models are regarded as among their respective approaches. The deep learning technique, which combines the deep features of VGG16 with SVM, produced accuracy and AUC values of 96.7% and 100%, respectively. The DWT method, Feature Extraction Based on Large Scale DWT with SVM, achieved an accuracy of 75.7% and an AUC of 90%. The performance of the classification model is also greatly improved with the implementation of the parallel feature fusion technique, with an accuracy of 98% and an AUC of 100%. This automatic grading method can be used to classify the papaya with respect to their maturity level and helpful for fruit industry.

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