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Characterising Colour Feature Descriptors for *Ficus carica* L. Ripeness Classification Based on Artificial Neural Network (ANN)

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ABSTRACT

Excessive feature dimensions impact the effectiveness of machine learning, computationally expensive and the analysis of feature correlations in the engineering area. This paper uses the colour descriptor to get the most optimal feature to improve time consumption and efficiency. This study investigated *Ficus carica* L. (figs) with three classification stages. The ripening classification of fig was examined using colour features descriptor with two different colour models, RGB and HSV. In addition, the machine learning classification model based on Artificial Neural Network (ANN) that utilised the Feed-Forward Neural Network (FFNN) model to classify the ripeness of fig is considered in this characterisation. Five different numbers of binning were characterised for RGB and HSV. Both colour feature descriptors were compared in terms of accuracy, sensitivity, precision, and time consumption to identify the dimension of the optimal feature. Based on the result, reducing the size of images will improve the time consumption with comparable accuracy. Moreover, the reduction of features dimension cannot be too small or too big due to inequitable enough to differentiate the ripeness stages and lead to

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a false error state. The optimal features dimension in binning for RGB was 8 (R/G/B) bins with 96.7% accuracy. Meanwhile, 96.7% accuracy for HSV at 15, 5, and 5 (H, S, V) bins as optimal colour features.

Keywords: ANN, colour descriptor, colour features, FFNN, fig, histogram, HSV, RGB, ripening

INTRODUCTION

Ficus carica L. (fig) is a fruit from the family of Moraceae, native to western Asia and the Mediterranean. Fig is also well-known for its benefit that cannot be denied. This fruit contains a high source of minerals, vitamins and fibre that are always used as dietary fibre as they are free from cholesterol and fat and contain many amino acids (Baigvand et al., 2015). Figs have a variety of families, such as Brown Turkey, Super Red Hybrid (SRH), Chicago Hardy, and Celeste. This kind of fig family will change its colour from green to brown or purple as the fruits ripen. In the other case, figs like Kadota, LSU Gold and Champagne have a green or yellow colour even though the figs are already mature.

Similar to other fruits, figs also undergo a ripening stage that could be categorised as climacteric fruit (Marei & Crane, 1971). It shows increased acidity level, ethylene production and respiratory response after harvesting (Marei & Crane, 1971). Furthermore, the significant changes during fruit ripening are becoming soft and the colour changes to less green (Skolik et al., 2019). Normally, a fig undergoes three ripening stages (Figure 1). In stage 1, fruits rapidly grow. While in stage 2, the figs will remain almost the same size, firmness, and colour. The last stage is stage 3, where the size of figs will grow to its maximum size while colour and texture change into an edible state (Freiman et al., 2015). According to Hssaini et al. (2019), the colour parameter exhibits an important variable in classification. More than 95% of their sample shows figs varying from green or yellow to purple.

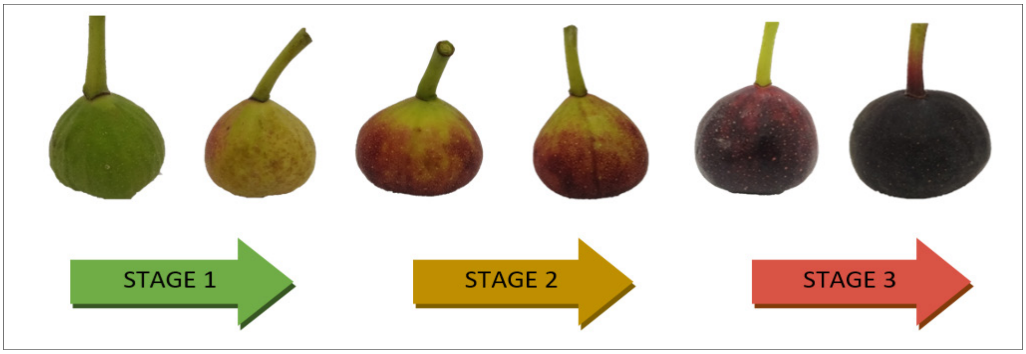


Figure 1. Ripening stage for figs based on colour changes

This study introduces a classification ripening stage of figs using image processing where the colour histogram approach is a colour descriptor based on RGB and HSV colour space. Images are the most basic way of physical prediction of the quality of fruits representing the conception of the human brain and are considered one of the fundamental steps for image improvement. Outside appearance can easily affect physical factors, including an inconsistent evaluation result. For example, the fruit's price was determined by the internal and external quality of the fruits or depending on the tag "best-if-used-before date." It could be why quality assessment of the fruits is a continuous task. Therefore, colour features have the potential to replace the conventional method of accessing quality parameters such as the ripeness of the fruits, as theoretically, the colour was obvious between the stages of ripeness (unripe, ripe, and overripe). Fast processing and low cost could be the main advantage of colour in the future (Taghizadeh et al., 2011).

RGB stand for red (R), green (G) and blue (B) channels in colour space, as shown in Figure 2. Combining these three channels will produce a resultant colour of the fruit (El Abbadi & San, 2013). The colour of the image can be obtained by adjusting the range between 0 to 255 (Pérez-rodríguez & Gómez-garcía, 2019). If all the channels demonstrated a pixel value at 0, the pure black colour would be shown, while the pixel value at 255 would represent all-white. HSV will provide a hue (colour depth or pure colour), saturation (amount of grey or purity colour) and value (colour brightness) in a colour space (Bargshady et al., 2020), as shown in Figure 2. Hue has a range of 0 to 360, and specific colours can be obtained by simply adjusting the Hue range. On the other hand, saturation shows a value from 0 to 100%, which refers to the purity of the colour. Value also takes the range from 0 to 100%, which refers to the brightness of the colour, where 0 is completely black, and 100 is the brightest and reveals the most colour (Hamuda et al., 2017). By combining these three parameters, a more specific colour can be obtained, for example, human skin tone or fruit skin colour (Hamuda et al., 2017).

RGB and HSV colour space can be classified using the histogram approach into specific bins that organise a group of data into a particular range (Hamdani et al., 2021) and be interpreted into a graph. For example, RGB colour space has a 256-intensity value and was binned into 4, 8, 16 and 32 according to a suitable value for the studies. For HSV, each channel for hue, saturation and value also can be grouped into a specific number of bins, such as 15 x 5 x 5 (Hue x Saturation x Value) or other binning values depending on the cases. This method helps a better resolution without losing any information and increases the number of accuracies (Bargshady et al., 2020; Hamdani et al., 2021). This study reported the ideal number of feature dimensions in bins colour histograms using a machine learning (ML) approach and handcrafted features based on RGB and HSV colour space.

Nowadays, image processing and machine learning (ML) are extensively used in agriculture as an essential approach corresponding to human vision in safely classifying the ripeness of fruits without destroying the shape and appearance of the fruits (Ortac et al., 2016). That could be why image processing and ML have picked the curiosity among research and become a trend nowadays. There is a variety of ML models that have been used widely in fruit classification, such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), k-Nearest Neighbour (k-NN), and Support Vector Machine (SVM) (Behera et al., 2020). All these methods depend on the characteristics and specifications of the researcher according to their studies. This type of algorithm data chosen depends on the data the researcher wants to classify.

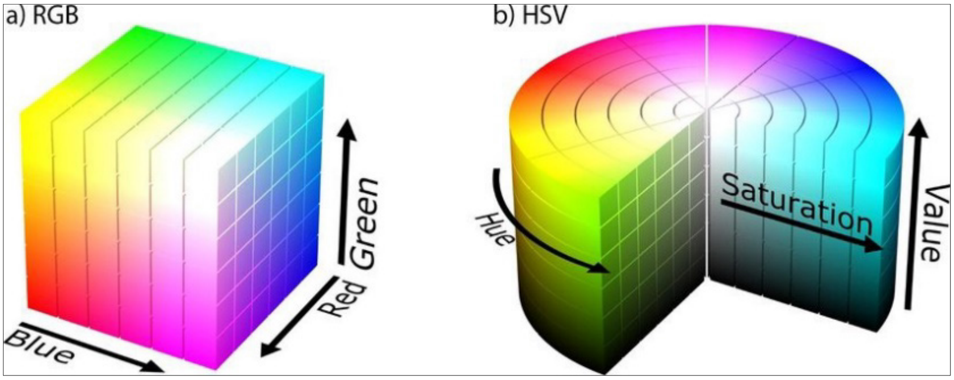


Figure 2. a) RGB and b) HSV colour feature descriptor model (Popov et al., 2018)

For the past few years, colour features and ML have been widely used in the agricultural industry to determine the ripening stage of fruits. Various fruits are used to evaluate the ripeness stage, such as apples, bananas, figs, grapes, lime, mango, oil palm, orange, papaya, peach, pineapple, strawberry, and sweet potatoes. According to previous researchers, the apple is one of the most popular fruits (Bratu et al., 2021; Tang et al., 2018; Song et al., 2020) and followed by of banana (Nguyen-Do-Trong et al., 2018; Zulkifli et al., 2019; Pu et al., 2019), orange (Li et al., 2016; Fermo et al., 2021; Bhosale, 2017) and peach (Yang et al., 2020; Minas et al., 2021). The least fruit was figs (Yijing et al., 2021; Bahar & Lichter, 2018), grapes (Cavallo et al., 2019), limes (Teerachaichayut & Ho, 2017), mango (Khalid et al., 2018), oil palm (Ali et al., 2020) and watermelon (Mohd et al., 2017). It would be the reason to discuss figs' ripeness classification; to the author's knowledge, only a few papers have discussed image processing on figs. Hssaini et al. (2019) are one of the researchers that investigated and considered taking figs as a study sample.

They used pomological and colourimetric traits derived from CIE measurement to characterise the type of figs based on qualitative and quantitative methods. As a result, ANN was used to classify the ripeness of fig fruit by using colour descriptors in this paper at three stages (unripe, ripe, and overripe). Besides, the research has only been done on colour features such as RGB. Considering different colour spaces using the colour histogram method could give an advantage in the figs gap of study. According to (Ikmal et al., 2021), no comprehensive work has been performed to utilise image analysis of figs to classify the various ripening stages using ANN. Therefore, the ideal colour features descriptor has been investigated in this paper using a similar suggested architecture of the ANN model to classify the ripening stage of figs.

RELATED WORK

Nowadays, the ripeness classification of fruits using image processing and ML is currently being developed continuously in agriculture. Effective data for image perception, interpretation, and object classification are extracted as a feature. Colour, texture, shape and morphological features are widely utilised to evaluate fruit defects and ripeness (Bhargava & Bansal, 2021). In a previous study, more than one feature extraction had been used. The most used were colour (Song et al., 2020; Nguyen-Do-Trong et al., 2018; Bahar & Lichter, 2018; Cavallo et al., 2019; Khalid et al., 2018; Nugroho et al., 2021; Sanchez et al., 2020; Munera et al., 2018; Manthou et al., 2020) texture (Nguyen-Do-Trong et al., 2018; Nugroho et al., 2021; Sanchez et al., 2020; Munera et al., 2018; Manthou et al., 2020), and size (Nugroho et al., 2021). Colour and texture were frequently and normally combined to get a better accuracy result (Septiarini et al., 2021). For example, Kangune et al. (2019) extract colour and texture to estimate grape ripeness using several neural networks models such as ANN, SVM and k-NN that give an excellent accuracy result. According to Fatima & Seshashayee (2022), the combination of features provides a better accuracy result where a multiple feature extraction method and extraction method at different ML model has been investigated in their study. Colour features can be extracted using RGB and HSV with the histogram binning method, as suggested by Hamdani et al. (2021). Both colour models have been tested and discussed in this paper.

Lately, several studies in ripeness classification have applied machine learning by Rady et al. (2017), which uses colour as a feature descriptor to detect the ripeness stages of the fruits. The Colour histogram approach (Hamdani et al., 2021) is based on RGB (Pérez-rodríguez & Gómez-garcía, 2019) and HSV (Bargshady et al., 2020; Hamuda et al., 2017) colour model had widely been used as image features to characterise and classify the fruits according to ripeness stages. Several studies would convert the RGB descriptor to another colour descriptor (i.e., HSV, HSL, and HSI). The combination of RGB and HSV also was often used in several studies to reach a better performance with higher frequency, as proposed by El Abbadi & San (2013). Therefore, the histogram binning approach used for both RGB and HSV descriptors has been discussed in this paper.

Several researchers used neural networks and machine learning to predict and classify fruits and vegetables. A study by Cho and Koseki (2021) proposed a deep learning method using the ANN model to determine the quality of bananas using image processing during the ripening stages. Prediction of the internal qualities of the banana was determined using different colour features such as HSV, luminance and chrominance extracted from RGB using the ANN model. Septiarini et al. (2021) developed a neural network model to classify oil palms based on colour and texture features using the ANN model to specify the maturity level. ANN with a back-propagation algorithm was applied in the classification process to obtain the prediction class. Worasawate et al. (2022) used ANN based on an ML classifier of feed-forward artificial neural network (FFNN) with a mean accuracy of 89.6% for classifying the ripeness stages of mangoes into three stages: unripe, ripe, and overripe. They used only colour features by evaluating different classifiers. Besides, a study from Magabilin et al. (2022) assesses multiple existing CNN models (MobileNetV2, VGG19 and Inception V3) to get the ideal model for classifying the Philippine Guyabano fruits based on colour features. After all, most researchers used colour features to assess the quality of fruits, especially in ripeness classification at different types of neural networks. It could be the reason that corresponds to this study's specific objective to find the ideal colour histogram binning either in RGB or HSV colour.

This paper compared and discussed the relationship between colour features and neural networks to classify the ripeness of figs according to the prediction class with a suitable number of feature dimensions in bins. The performance for each bin will be evaluated in terms of accuracy and classification performance. The procedure of this investigation will be explained more in methodology.

METHODOLOGY

In this paper, colour features have been investigated and discussed to classify the ripeness of the figs. The general procedure of this study is shown in Figure 3, where the raw image of 30 figs was taken from six different angles (Ikmal et al., 2021). Then, each image undergoes a pre-processing stage where the resizing happens. It is based on the trade-off between processing time and the size of images at the initial classification stage in machine learning (ML).

Subsequently, the colour feature of the image will be extracted by using RGB and HSV colour space as colour descriptor characterisation. Each RGB and HSV descriptor will employ the colour histogram method for each channel into a dedicated number of bins. The features dimension will be reduced to five different numbers in a set of bins for both RGB and HSV to conclude the best colour descriptor to be used in this study, and the performance will be discussed in this paper. Artificial Neural Network (ANN) was used as a handcrafted feature in these studies to predict the ripening stage. The number of features dimension was investigated to achieve a better computational time with a great classification performance. Lastly, extracted features will undergo classification performance evaluation, such as accuracy, sensitivity, and precision.

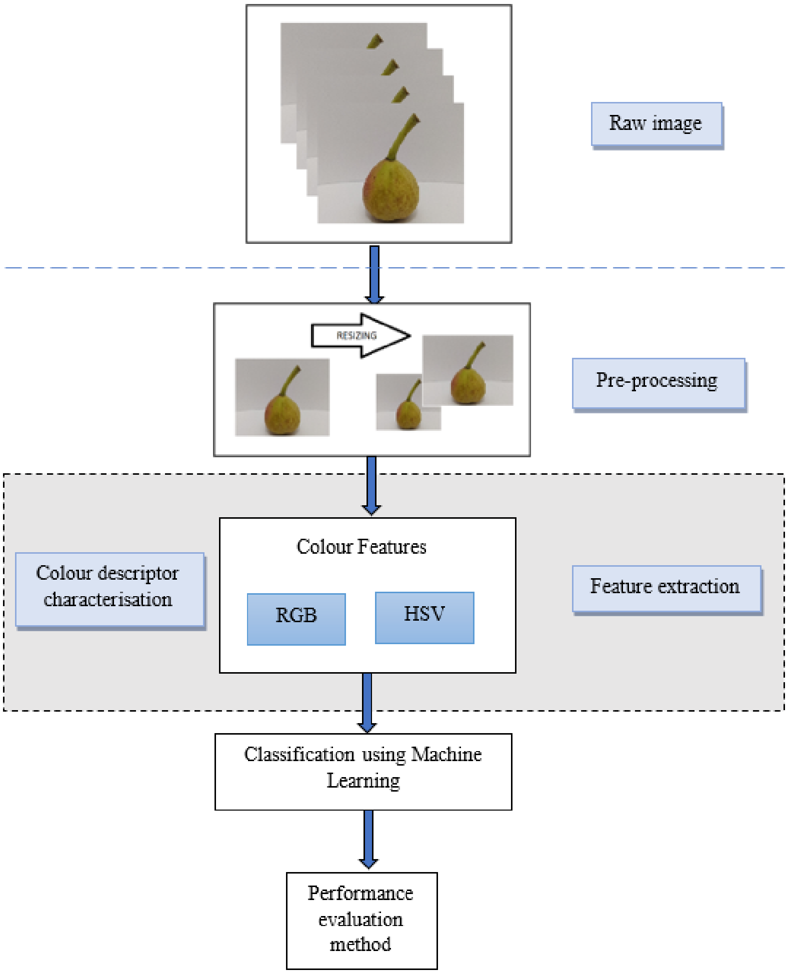


Figure 3. The process of ripeness classification using colour features for figs

Experimental Data Preparation

The dataset of this study was derived from the figs' skin colour to classify the ripeness. The image acquisition techniques for figs images were taken in a small studio setup by Ikmal et al. (2021), using a smart mobile phone stand to maintain the same distance as the fruits. The backgrounds are white with bright light to perform a better-quality image to prevent any unforeseen occurrence or wall texture from disturbing the images. Initially, 30 sets of figs with the same type of fig family, which is Super Red Hybrid (SRH), were collected from a fig farm and classified according to three-stage (10 for stage 1, 10 for stage 2 and 10 for stage 3) of figs ripeness (unripe, ripe, and overripe) by the expert. Then, each fig was photographed at six different angles (left, right, top, bottom, back and front) (Figure 4). As a result, 180 (30 x 6) images with 4000 x 3000 pixels are acquired to extract colour features.

Next, each of the images has been resized into five different sizes, which are default size 4000 x 3000), reducing to 50% (1500 x 2000), 80% (600 x 800), 90% (300 x 400) and 98% (60 x 80) size for RGB and HSV colour descriptor. The biggest size will be 4000 x 3000 or default, while the smallest one will be 60 x 80. These different sizes will be used to investigate the time consumed even though, and theoretically, the bigger image size will consume more time. This result will help for further investigation of colour descriptor performance. Lastly, two different sizes (default and smallest) will be evaluated in terms of accuracy, sensitivity, and precision.

Feature Extraction

The main objective of this paper is to classify the ripeness of the figs using colour features that act as a good descriptor (Hamdani et al., 2021). The image of each fig has been extracted using RGB and HSV colour descriptors using the colour histogram method. Five different numbers of bins were tested for each colour model (RGB and HSV).

RGB

RGB colour model involves three channels: Red, Green and Blue. RGB consists of 256 levels, and each colour channel will be histogrammed into several bins (4, 8, 16, 32 and 64) (Figure 4). For example, if the number of bins is 8, then about 32 levels of intensity will be grouped into one bin. Then, the number of features will be binned according to a specific range to become one dimension (1D) feature vector that concatenates six features from each fruit angle (Figure 4). The total features vector (γ) for eight bins will be 144 dimensions have been extracted as this number can be obtained from Equation 1:

$$\gamma = a \times b \times c \quad , b = 3 \tag{1}$$

where γ is the total feature vector, ‘a’ is the number of bins, ‘b’ is the number of channels is three represents each red, green and blue channel. Every fig fruit undergoes six angle images that had been taken, which represent ‘c.’ The value of α is the total dimension from each angle of fruits which is the total of (a x b) (Figure 4).

HSV

Similar to RGB, different numbers of histogram bins will also be tested in the HSV colour model. HSV consist of three channels: hue (H), saturation (S), and value (V). These channels can be converted from RGB (Hamdani et al., 2021) by using Equations 2 to 5:

$$H = \begin{cases} \theta, & B \leq G \\ 360 - \theta, & B > G \end{cases} \tag{2}$$

$$\theta = \cos^{-1}\left\{\frac{\frac{1}{2}(R-G)+(R-B)}{[x(R-G)^2+(R-B)(G-B)]^{1/2}}\right\} \tag{3}$$

$$S = \begin{cases} 0, & max(R, G, B) = 0 \\ 1 - \frac{min(R, G, B)}{max\,(R, G, B)}, & otherwise \end{cases} \tag{4}$$

$$V = max f_0\,(R, G, B) \tag{5}$$

Some five different combinations of bins for each channel had been tested for HSV. The combinations are (13, 3 and 3), (14, 3 and 3), (15, 5 and 5), (16, 4 and 4) and (17, 6 and 6). Then, these features were reshaped into 1D with a total value (H x S x V). For example, if the value of the bin is 16, 4 and 4 for the H, S and V, respectively. Then the total value (α) becomes 256. Since the total image angle for each fig fruit is 6, the features vector was concatenated as shown in Figure 4, similar to RGB.

The total dataset of the feature vector is 30 x γ, and every value of the features vector will be labelled according to ripeness level (phases 1, 2 or 3).

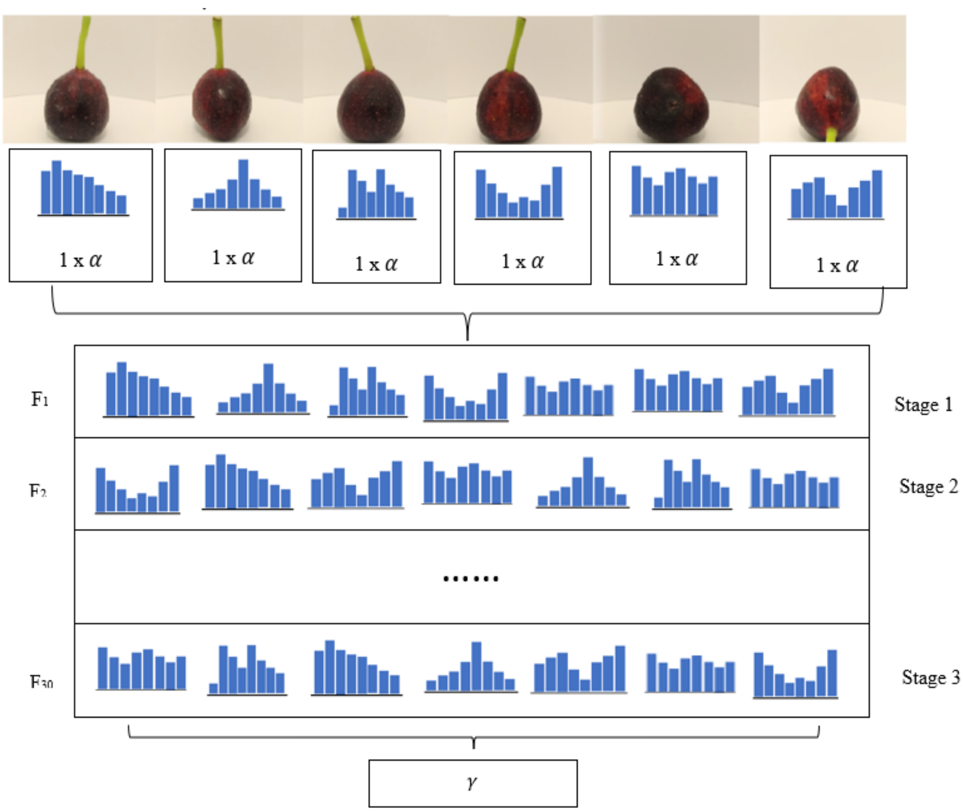


Figure 4. Example of 30 sets of figs extracted using colour features

Artificial Neural Network (ANN)

ANN classification model was used in this paper to predict and classify the ripeness stage based on colour features extracted from the fig fruit images. Based on the classification or pattern recognition technique, identifying in the context of ripening fruit stages was implemented by using Feed-Forward Neural Network (FFNN) model. RGB and HSV descriptors were trained to extract the feature from fig images.

The structural framework of FFNN was divided into three layers: an input layer, a hidden layer and an output layer (Figure 5). This model's training algorithm helps minimise the layer's error, highly responsive data, fast and less complex (Rady et al., 2017).

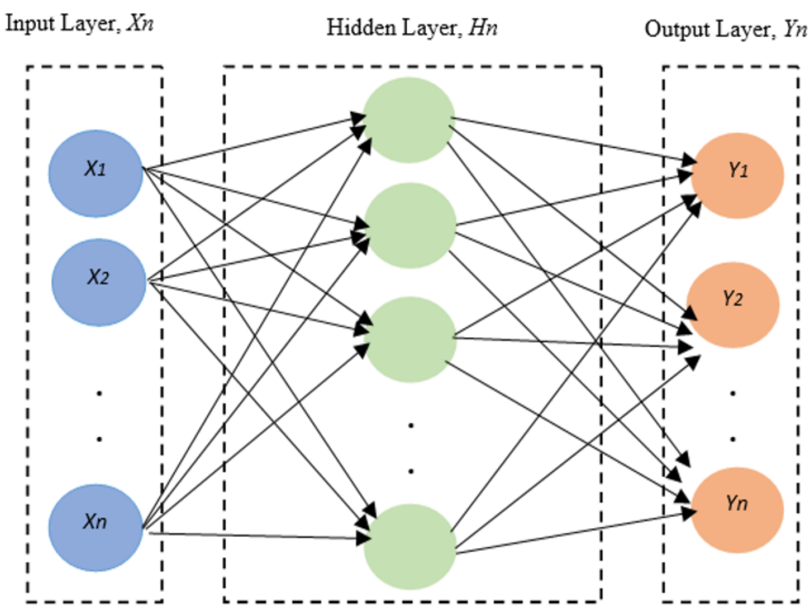


Figure 5. Typical model of Feed-Forward Neural Network (Ikmal et al., 2021)

The number of neurons or hidden nodes used in the hidden layer was set to default 10. The higher number of neurons, the highest the learning improvement of FFNN to classify the ripeness stages was computationally expensive. The input layer was the number of total dimensions at the extracted features containing spectral data, and the output layer contained the assigned stage (stage 1, stage 2 and stage 3). The transfer function for hidden and output layers undergoes log-sigmoid and scale gradient back-propagation respectively (Rady et al., 2017). The process of training a neural network that assigns the correct target classes or stages with input patterns is known as pattern recognition. Once trained, the network can classify the pattern it has not seen before.

Training Methodology

The sample of figs had been divided into three learning stages: Training, Validation and Testing. Training configuration had been set accordingly (Table 1). During the training stage, 70% of the sample is submitted to the network, which is changed based on inaccuracy. Then 15% of the samples are selected for validation and testing. Validation samples track the network generalisation and cease training when the generalisation plateaus. Hence, a testing sample will measure the network performance independently after the training phase. The number of hidden nodes was set up to 10 neurons (Ikmal et al., 2021) in this configuration for each RGB and HSV colour feature.

The number of 10 neurons was chosen according to the investigation by Ikmal et al. (2021) with a different number of neurons.

Table 1
ANN training configuration setup

CPU	AMD Ryzen 5 4600U
GPU	Radeon 2.10GHz
RAM	8.00 GB
Operating system	64 bits
Processor	X64-based processor
OS	Windows 10
Software	MATLAB R2021a
Machine learning	Neural Network Pattern Recognition
Features	RGB and HSV colour model
Hidden nodes	10 neurons (Ikmal et al., 2021)

Performance Evaluation Method

The descriptor of the colour features to classify the ripeness of figs was evaluated using sensitivity, precision and accuracy. Each number of bins used for both RGB and HSV colour descriptor were reported in this paper. The Machine Learning (ML) classification problem can be concluded using a confusion matrix. Each row and column correspond to a predicted and actual class that reports true positive (TP), false positive (FP), false negative (FN) and true negative (TN). Then, the count of the correct or incorrect data sample (training, validation or testing) filled up Table 2. The confusion matrix result shows the value of sensitivity, precision, and accuracy, as shown in Equations 6 to 11.

$$Sensitivity\ (S) = \frac{TP}{TP + FN} \tag{6}$$

$$Average\ sensitivity = \frac{s_1 + s_2 + \ldots + s_n}{n} \tag{7}$$

$$Precision\ (P) = \frac{TP}{TP + FP} \tag{8}$$

$$Average\ precision = \frac{P_1 + P_2 + \ldots + P_n}{n} \tag{9}$$

$$Accuracy\ (A) = \frac{TP + TN}{TP + FP + FN + TN} \tag{10}$$

$$Average\ accuracy = \frac{A_1 + A_2 + \ldots + A_n}{n} \tag{11}$$

Table 2
Example of the confusion matrix table

	Actual positive (1)	Actual negative (0)
Predicted Positive (1)	True Positive (TP)	False Positive (FP)
Predicted Negative (0)	False Negative (FN)	True Negative (TN)

The sensitivity, known as recall, where the positive class mattered the most compared to the negative, is similar to precision. Accuracy is used to evaluate the ratio of a correctly predicted data sample to the total data sample.

RESULT AND DISCUSSION

The proposed method using a colour descriptor was examined to study the relationship of colour features with classification performance using the ANN model. The classification performance of sensitivity, precision and accuracy in a percentage has been evaluated in this paper.

This study starts by investigating the time consumption with different sizes of images. The image size was resized or reshaped from a default size (3000 x 4000) to four other different sizes by reducing it to 50% (1500 x 2000), 80% (600 x 800), 90% (300 x 400) and 98% (60 x 80) size for both RGB and HSV colour descriptor that had been evaluated as shown in Figure 6 and Figure 7. The result of time consumed demonstrated as the bigger size of the image, the more time consumed will be increased. It is a fact that reducing the size will also reduce time consumption. Nevertheless, we are interested in investigating colour descriptors' accuracy and performance while the size is reducing. The other performance classification method was examined to align with this result.

Two sizes of RGB and HSV were selected, the default and the smallest, to see whether the performance was affected in terms of accuracy and classification performance. Surprising, that the size did not necessarily impact the performance, as shown in Figure 8. The average accuracy for RGB and HSV between the two sizes has a narrow gap of accuracy value in a percentage ranging from 93.3 to 97.6%. In addition, the HSV colour model has a slightly higher accuracy value, which is more accurate at 97.6%, while RGB is 95.6%. It proved what had been mentioned by Wu et al. (2020), where HSV is better suited in colour recognition as it is very similar to human perception of distinct colour features if compared to RGB.

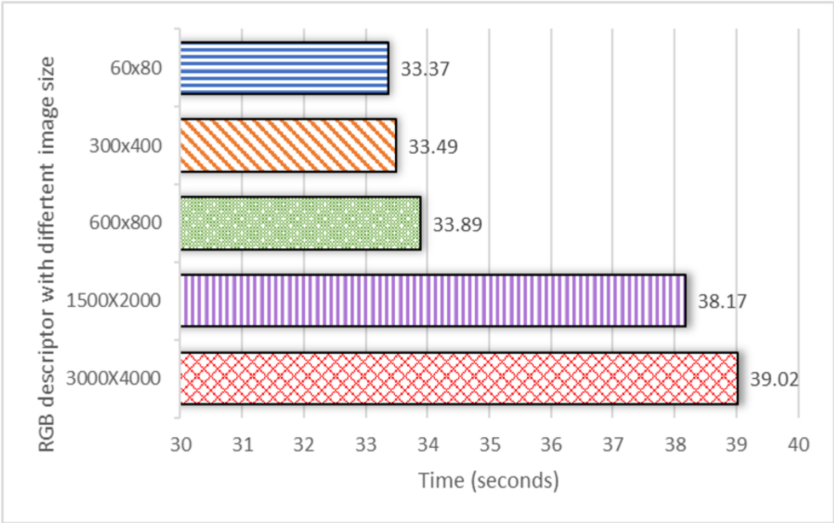


Figure 6. Time consumed for different RGB image sizes

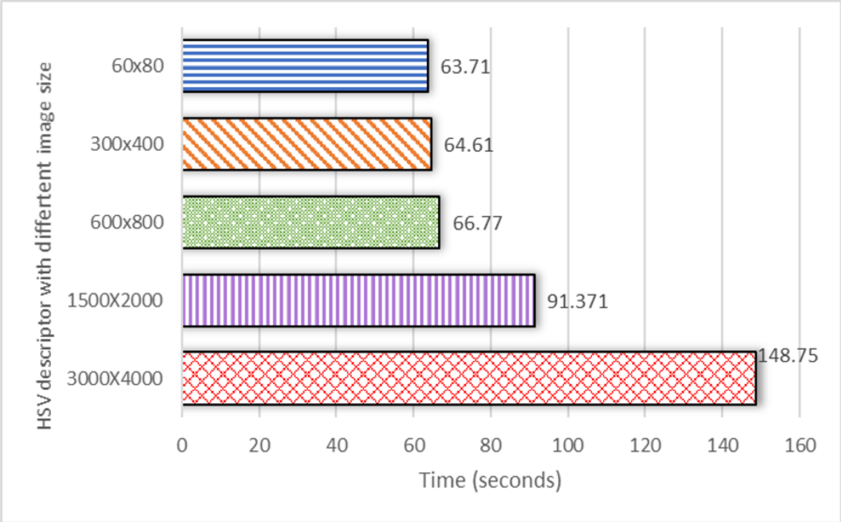


Figure 7. Time consume for different HSV image sizes

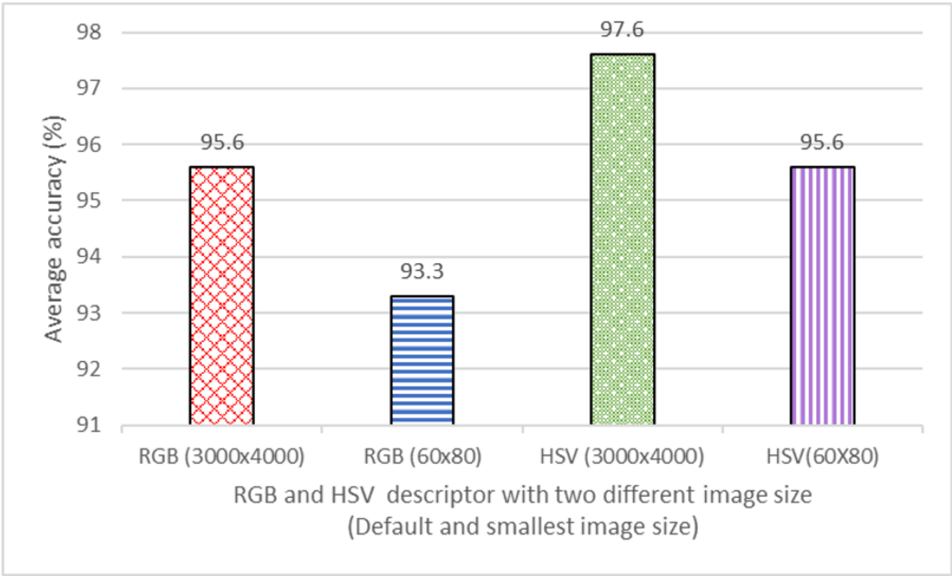


Figure 8. RGB and HSV average accuracy with two different image sizes

The performance classification method for the RGB colour model with two different sizes (default size and smallest size) was evaluated (Tables 3 and 4). The evaluation method was examined using several features extracted set at bins 4, 8, 16, 32 and 64, which were then classified using a neural network.

Table 3
RGB sensitivity, precision and accuracy value at 3000 x 4000 image size

No. of bins. (R/G/B)	Sensitivity (%)			Precision (%)			Accuracy (%)
	Stage 1	Stage 2	Stage 3	Stage 1	Stage 2	Stage 3	
4	83.3	100	90.9	100	70.0	100	90.0
8	100	90.9	100	90.0	100	100	96.7
16	90.9	100	100	100	90.0	100	96.7
32	83.3	100	100	100	80.0	100	93.3
64	71.4	100	71.4	100	20.0	100	86.7

Table 4
RGB sensitivity, precision and accuracy value at 60 x 80 image size

No. of bins. (R/G/B)	Sensitivity (%)			Precision (%)			Accuracy (%)
	Stage 1	Stage 2	Stage 3	Stage 1	Stage 2	Stage 3	
4	90.0	80.0	90.0	90.0	80.0	90.0	73.3
8	90.9	100	90.9	100	80.0	100	93.3
16	90.0	90.0	100	90.0	90.0	100	93.3
32	81.8	88.9	100	90.0	80.0	100	90.0
64	90.9	100	76.9	100	60.0	100	73.3

Sensitivity and precision were evaluated in each stage (1, 2 and 3). The value of sensitivity and precision is low, especially in stages 1 and 2. It is because, as mentioned before, the colour of stage 1 and stage 2 has a colour that is nearly the same. Nevertheless, the average value was quite good (Figure 9). The sensitivity, known as recall, reflects the ability to recognise a positive sample. The highest average sensitivity value was 97% for the default image size and 93.3% for the smallest image size. Meanwhile, the lowest average sensitivity was 80.9% for the default image size and 86.7% for the smallest image size. The average precision used to evaluate the classification accuracy of positive samples with the highest value is 96.7% for the default image size and 93.3% for the smallest size. The lowest value was 73.3% and 86.7% for both sizes, accordingly. The highest percentage obtained for sensitivity and precision was highest when the image size was 3000 x 4000 (default size) compared to the smaller image size. Five different numbers of bins were investigated, and for performance evaluation, the lowest accuracy value was 86.7% at bins 64, while 73.3% at bins 4 and 64 when the size was reduced (Tables 3 and 4). It proves bin 4 is inequitable enough to differentiate the ripeness stages for figs, and bin 64 is too big that tends to have a false rate. Meanwhile, the highest accuracy values were 96.7% and 93.3% which were used in bins 8 and 16. The result shows that bins 8 and 16 are ideal for colour feature descriptors in the RGB colour model.

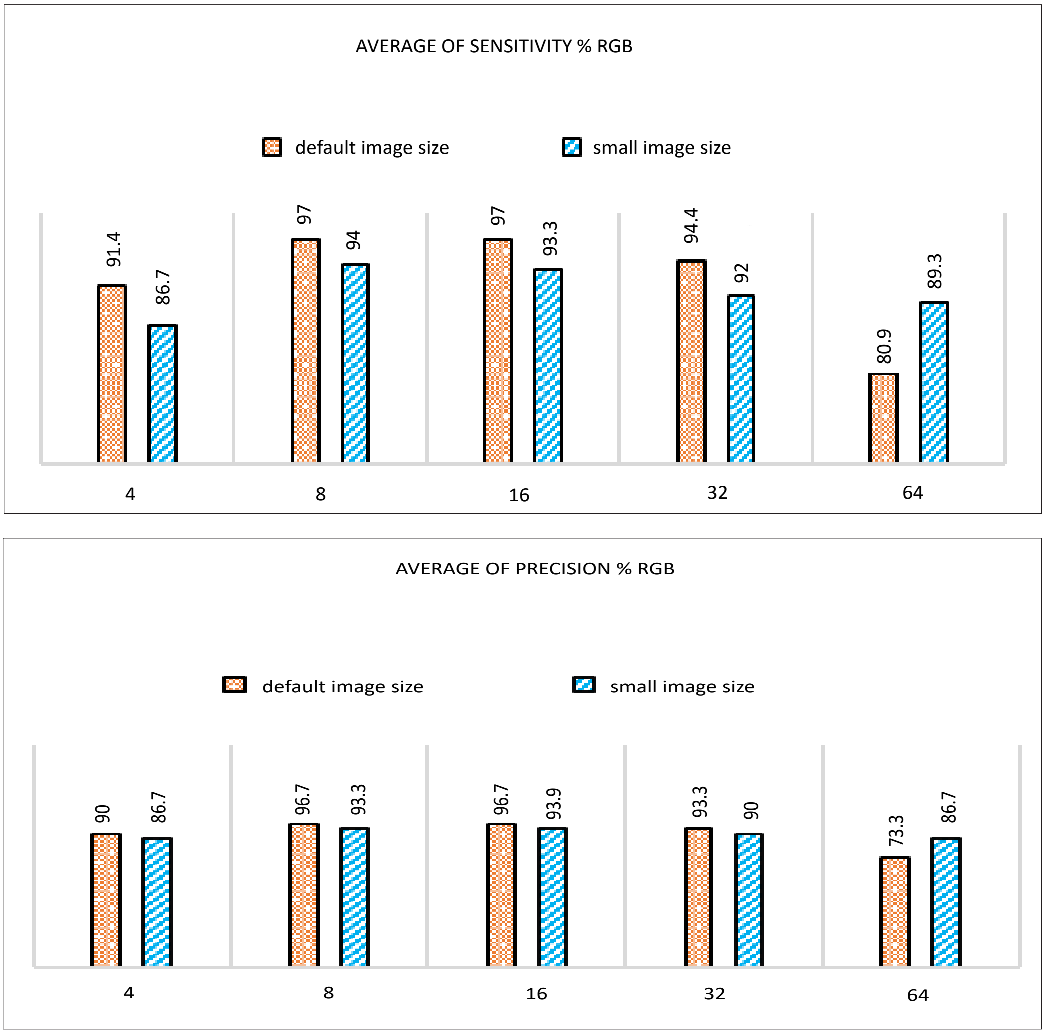


Figure 9. Average of sensitivity and precision in percentage for RGB colour model

The performance classification method for the HSV colour model with two different sizes was also evaluated (Tables 5 and 6). Similar to RGB, the value of sensitivity and precision in the HSV colour model was examined for each ripeness stage at two different sizes (default size and smallest size). Several features were extracted using five different sets of bins: (13, 3, 3), (14, 3, 3), (15, 5, 5), (16, 4, 4) and (17, 6, 6) also were examined. The average result for each stage in sensitivity and precision is illustrated in Figure 10.

Table 5

HSV sensitivity, precision and accuracy value at 3000 x 4000 image size

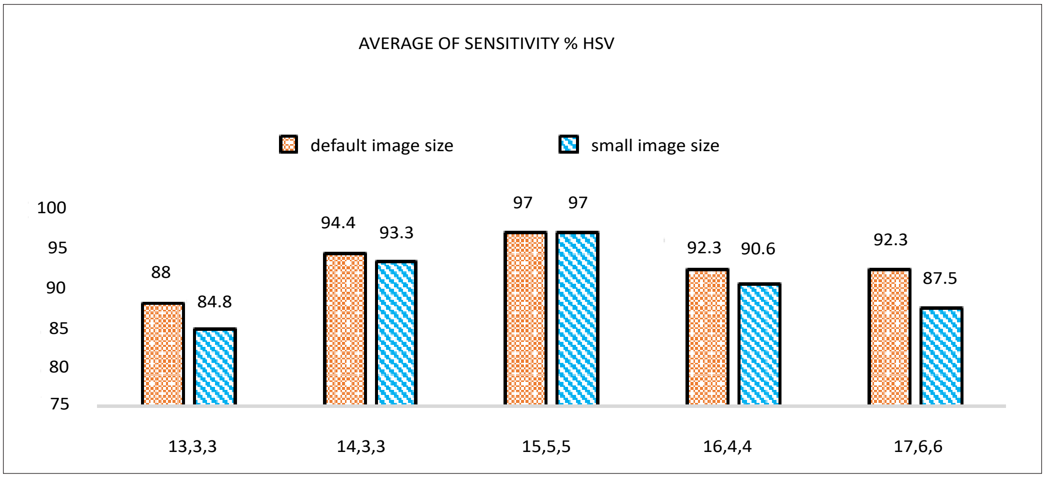
No of bins (H, S, V)	Sensitivity (%)			Precision (%)			Accuracy (%)
	Stage 1	Stage 2	Stage 3	Stage 1	Stage 2	Stage 3	
13, 3, 3	88.9	75.0	100	80.0	90.0	90.0	86.7
14, 3, 3	100.0	83.3	100	80.0	100	100	93.3
15, 5, 5	90.9	100	100	100	90.0	100	96.7
16, 4, 4	100	76.9	100	90.0	100	80.0	90.0
17, 6, 6	100	76.9	100	70.0	100	100	90.0

Table 6

HSV sensitivity, precision and accuracy value at 60 x 80 image size

No of bins (H, S, V)	Sensitivity (%)			Precision (%)			Accuracy (%)
	Stage 1	Stage 2	Stage 3	Stage 1	Stage 2	Stage 3	
13, 3, 3	72.7	81.8	100	80.0	90.0	80.0	83.3
14, 3, 3	90.0	90.0	100	90.0	90.0	100	93.3
15, 5, 5	100	90.9	100	90.0	100	100	96.7
16, 4, 4	90.0	81.8	100	90.0	90.0	90.0	90.0
17, 6, 6	87.5	75.0	100	70.0	90.0	100	86.7

The average sensitivity values were 97% (default size) and 93.3% (smallest size). Meanwhile, the lowest sensitivity was 88% (default size) and 84.8% (smallest size). Similar to RGB, the default image size shows a better average sensitivity and precision result than small image sizes. It can conclude that the default image was better without resizing as the number of pixels and intensity could be changed and lead to the lowest result. The lowest accuracy was 86.7% (default size) and 83.3% (smaller size), which were obtained from a set of bins (13, 3, 3) and (17, 6, 6). Having too many numbers and too small of features extracted would be difficult for the model to classify the differences in ripeness stage based upon their characteristic. The highest accuracy values were 96.75% and 93.3% for the bins (14, 3, 3) and (15, 5, 5). For the HSV colour model, the features extracted bins (14, 3, 3) and (15, 5, 5) were concluded to have a good performance.



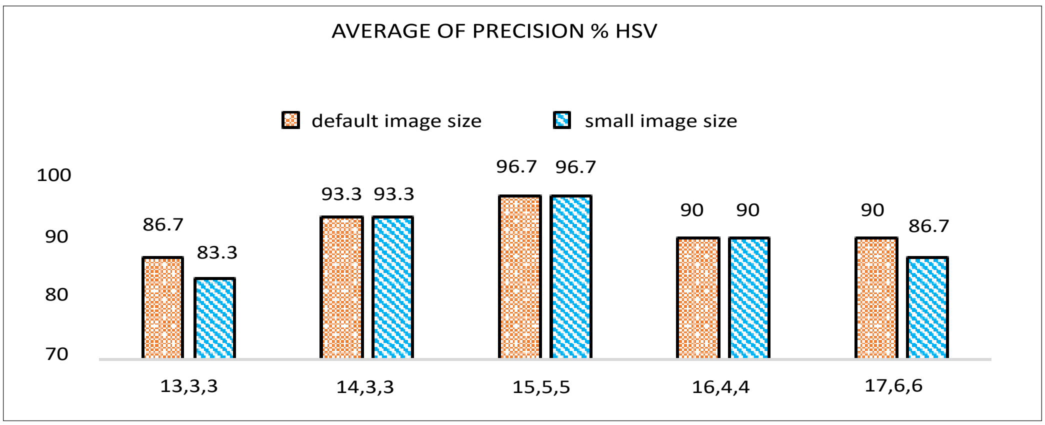


Figure 10. Average of sensitivity and precision in percentage for HSV colour model

The difference between RGB and HSV can be concluded by considering the overall performance evaluation method, where HSV has the highest average accuracy, sensitivity and precision as the colour features descriptor of figs ripeness classification.

CONCLUSION

In conclusion, the classification of figs' ripeness was examined using colour features descriptor for both RGB and HSV colour models. About 30 figs with six different angles were trained using ANN with a base of the FFNN model as a pattern recognition and classification model to determine the ripeness stages of figs. The reduction of features dimension was investigated using histogram binning with five different numbers of bins for both colour models. The ideal number of bins for dimension features for RGB was 8 and 16, with an average accuracy of 96.7% and 93.3%. Meanwhile HSV colour model has 96.7 % for HSV at the 15, 5, 5 (H, S, V) bin set. The value of sensitivity and precision also had been examined throughout this study. The highest value for sensitivity was 97%, and precision was 96.7% for RGB (8 and 16) and HSV (15, 5, 5) bins, respectively. In addition, reducing the image size and feature dimension did not degrade the performance as the accuracy was above 90%, which also helped to reduce the time consumption. However, the result shows HSV has a better average accuracy result due to the sensitivity of hue, saturation and value in colour space. For future work, texture and colour as combination features would be envisaged to increase the performance of ripeness classification. Besides, we suggest using a different machine learning approach, such as Convolutional Neural Network (CNN), to distinguish the appearance in terms of ripeness stages to correspond colour descriptors with image features of figs. It is due to image features correlating with a colour descriptor, especially for figs, which are seldom discussed.

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