International Journal of Engineering & Technology, 7 (4.31) (2018) 452-458

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

Fruits Recognition based on Texture Features and K-Nearest Neighbor

Nur Izzani Kamal Ariffin[1], Mas Rina Mustaffa[2]*, Lili Nurliyana Abdullah[3], Nurul Amelina Nasharuddin[4]

Multimedia Department, Faculty of Computer Science and Information Technology, Universiti Putra Malaysia, 43400 UPM Serdang, Selangor Darul Ehsan, Malaysia
**Corresponding author Email: MasRina@upm.edu.my*

Abstract

Malaysia is well-known for its variety of fruits available in the country such as pineapple, guava, durian, apple, and watermelon. Therefore, it is important for us to get to know more about fruits so that we can take advantage of all the benefits that each fruit can offer. However, problems may arise where a person may know nothing about a particular fruit apart from only having an image of it. Most of the fruit encyclopedias nowadays still rely on text as search input. Furthermore, various features are commonly utilised for representation which can lead to high computational complexity. Therefore, to overcome these problems, a content-based texture-only fruits recognition that accepts an image as input instead of text is proposed. A framework which extracts five texture features (homogeneity, energy, entropy, correlation, and contrast) based on Gray-level Co-occurrence Matrix (GLCM) descriptor is constructed. *k*-Nearest Neighbour (*k*-NN) is used at the classifier model to determine the type of fruits. The conducted empirical study has shown that the proposed work has the ability to effectively recognize fruit images with 100% accuracy.

Keywords: *Fruits recognition; Gray-level Co-occurrence Matrix; k-Nearest Neighbor; texture features.*

1. Introduction

Recognition is one of the main parts in computer vision where it produces high level of understanding by computers. As our daily life is getting more computerised, automatically it makes the recognition systems become a need. There are many recognition systems that have been developed such as for face [1-2], voice [3], handwriting [4], and others [5-7]. One of the essential parts in recognition is object recognition, which is a process for recognising a specific object in a digital image or video [8]. A recognition framework comprises of several components which include feature extraction and machine learning.

Feature extraction is the process of obtaining high level information of important object in an image [8]. There are three features that have been used for describing image content which are texture, colour and shape. Texture is a significant feature that recognises the object existent in any image. It is characterised by the spatial distribution of pixels in a neighbourhood of an image. Colour feature is extensively used for image extraction. This is because of the simplicity to extract colour information. Shape feature is also widely used in recognition system. Therefore, all these features have their own capability and play an important role in extracting image content.

Machine learning is a data analytic method that allows computers to learn without being explicitly programmed. Machine learning helps human in making better decisions or predictions by finding natural patterns in data. There are two types of machine learning algorithm which are supervised and unsupervised [9]. Supervised learning is used when we want to train a model to make predictions for the response of new data. In contrast, unsupervised learning is used when the information used to train is neither classified nor labelled.

Fruit is one of the agriculture components that have high demand over the world. There are varieties of fruit available in this world such as pineapple, guava, apricot, apple, and watermelon. Each of these fruits has different characteristics in terms of their texture, colour and shape that we can use to differentiate each of them. Fruits recognition is important for many reasons such as for automatic fruit harvesting or fruit quality control. Few existing works on fruits recognition are reviewed and discussed.

The fruits recognition proposed by Seng and Mirisaee [8] is based on the combination of colour, shape, and size of fruits. The extracted values of colour, shape and size features are then used to calculate the distance between the computed feature values of query image with the feature values of each fruit images in the training set. *k*-Nearest Neighbour (*k*-NN) classification is used to categorise the fruit images based on the computed feature values. There are five main modules in this work. The first module is fruit input selection where it will prompt the user to choose a fruit image from the selection menu in order to proceed with the recognition process. Next is fruit colour computing module, this is where the colour features of fruit will be extracted. The area and perimeter of a fruit image are used in shape roundness computation during fruit shape computing module. The fruit size computing module is important to calculate the size of fruit. The fifth module is classification module. The task of this module is to categorise the input fruit image based on Euclidean distance and *k*-NN method. The recognition result of the fruits recognition system that has been proposed is up to 90% accuracy. However, there are several things that can be implemented in future to make this system more robust and effective to recognise fruit images. For training set, more fruit images of different types should be collected to train the system. Besides, training images also should be in different angles and position so that it can recognise just any type of fruit images.

Authors in [10] employs colour and size to differentiate between different types of fruits and vegetables. There are four steps involved in the implementation phase. First step is the learning process where images are converted to HSV model to avoid illumination effects and the histograms for each image are computed. Second step is capturing an image of fruit and vegetable to be recognised. After capturing the image, the same steps as in the learning process are repeated. Third step is comparing between learnt images and captured image. The histogram of captured image and histograms of learnt images were compared to each other using the minimum-distance classifier, Chi-square method. Finally, the matching image is found based on the previous results of histograms comparison. This application showed an accuracy of 75% in recognising fruits image. The accuracy could probably be improved by incorporating other features like texture.

The work explained in [11] is about date fruits classification based on texture and shape features. The steps that involved in this work are pre-processing, selecting part of fruit, texture and shape extractions and lastly classify the dates with supervised classifier, *k*-NN. Before image extraction, the specular reflection and noise are reduced by using bilateral filter. For shape extraction, six shape attributes are calculated which are area, perimeter, major and minor axis length, eccentricity and finally equidiameter. The fruit contour is used to extract the shape of date fruits. Texture is one of the important features that describe about the variation pattern of surface. To extract texture of the date fruits, Local Binary Pattern (LBP) and Curvelet Transform have been used. The proposed approach achieves up to 96.45% of grading accuracy.

Authors in [12] utilised the Bag-of-Feature (BoF) model for almond feature representation where they experimented with few keypoint detectors such as Harris, Harris-Laplace, Hessian, Hessian-Laplace, and Maximally Stable External Regions (MSER) together with Scale Invariant Feature Transform (SIFT). K-means clustering is then used to build the codebook from keypoint descriptors. Various codebook size is also being experimented. Three classifiers were tested on 2000 sweet and bitter almonds (K-NN, Linear SVM, and Chi-square SVM) which were randomly sampled from an almond orchard in a commercial farm in Yazd, Iran. It has been observed that the Harris-Laplace combined with SIFT descriptor, with a codebook size of 500, and Chi-SVM provides a reasonable recognition accuracy of 97.5% for sweet almonds and 95.5% for bitter almonds.

From the studies, it can be observed that most of the past works usually recognise fruits based on their shape or colour or combination of various features. This can lead to higher computation complexity. However, it is very seldom where fruits are being recognised based on texture individually without combining with other features. Therefore, the research question is that can fruits be recognised based on its texture only? Thus, this paper will focus on developing a content-based representation for fruits recognition based on texture-only features. The outline of this paper is as follows. Section 2 explains the related work while Section 3 describes the proposed framework. The fruits recognition system is explained in Section 4 while the framework for evaluation and analysis of results are discussed in Section 5. Finally, the conclusion and future direction are presented in Section 6.

2. Related Work

In statistical-based texture descriptors, texture components are measured from the statistical distribution of observed combinations of intensities at specified positions relative to each other in the image [13]. The Gray-level Co-occurrence Matrix (GLCM) is formulated to compute texture feature extraction. The GLCM is one of the most well-known method and widely used in image processing and pattern recognition. Fig. 1 (a) visualises the calculation of GLCM for the sample input. This example is computed with an angle $\Theta=0°$ and distance $d=1$. Position (1,1) in Fig. 1 (b) contains the value 1 because there is only one pair of 1 and 1 in sample input according to the selected Θ and d. All the GLCM values for the sample input are calculated following the same way.

According to Haralick et al. [14], there are 14 textural features that can be computed and derived from the co-occurrence matrix. These features are angular second moment, contrast, correlation, sum of squares, inverse different moment, sum average, sum variance, sum entropy, entropy, difference variance, difference entropy, information measures of correlation I, information measures of correlation II, and maximal correlation coefficient. Each of the features has its own general usability for different type of images.

The *k*-Nearest Neighbours (*k*-NN) is one of the simplest algorithms that are used commonly for classification. *k*-NN has been used in a huge number of fields such as pattern recognition, image recognition and statistical estimation. *k*-NN will classify the training images data into a particular group based on their feature vector values. *k*-NN algorithm acts as a classifier that performs classification by computing the distance measure. The most widely used for distance measure is Euclidean distance, where it calculates the distances between the feature vector of test image with stored feature vector of training images. *k*-NN will determine the *k* shortest distance or nearest examples to the input test image then allocate the input test image to the group where majoring of the *k* nearest neighbours is from [8].

1	1	3	6	3
2	3	5	7	1
4	5	7	1	2
3	5	1	2	3

(a)

G L C M

	1	2	3	4	5	6	7	8
1	1	2	0	0	1	0	0	0
2	0	0	1	0	1	0	0	0
3	0	0	0	0	1	0	0	0
4	0	0	0	0	1	0	0	0
5	1	0	0	0	0	1	2	0
6	0	0	0	0	0	0	0	1
7	2	0	0	0	0	0	0	0
8	0	0	0	0	1	0	0	0

(b)

Fig.1: Gray-level Co-occurrence Matrix (GLCM) Implementation. (a) Sample input, (b) GLCM Values for the Sample Input

3. Proposed Framework

The proposed fruits recognition framework can be separated into two phases which are training phase and testing phase. Before recognition of fruits can be done accurately, the *k*-Nearest Neighbour (*k*-NN) classifier will need to be trained using the training fruit images. Fig. 2 shows the processes involved for training and testing the predictive model which will be used for recognising fruits.

Based on the proposed framework, Gray-level Co-occurrence Matrix (GLCM) method is used for feature extraction. The system has to read an input image before starting the feature extraction process. The input image will undergo pre-processing where it will convert the RGB image into gray scale image. This is necessary because the dimension of a GLCM is determined by the maximum gray value of the pixel in an image. Therefore, the number of gray levels is a significant element in GLCM calculation. After the GLCM has been computed, few statistical-based features are extracted to provide different details of the image as representation. According to Haralick et al. [14], there are 14 statistical-based descriptions which can be extracted. For this work, we are constructing only five features which include contrast, energy, entropy, homogeneity and correlation. These features can be generated based on the Equations (1) – (5) below.

$$Contrast = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}(i-j)^2 P_{i,j} \quad (1)$$

$$Energy = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}(P_{i,j})^2 \quad (2)$$

$$Entropy = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} P_{i,j} \log P_{i,j} \quad (3)$$

$$Homogeneity = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{P_{i,j}}{1+|i-j|} \quad (4)$$

$$Correlation = \frac{1}{\sigma_x\sigma_y}\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\left[(i,j)P_{i,j} - \mu_x\mu_y\right] \quad (5)$$

Where μ_x, μ_y, σ_x, and σ_y are the means and the standard deviations of the corresponding distributions. *G* is the number of gray levels. These features are selected based on a conducted empirical study (results can be observed in Section 5). The extracted features will form the feature vector for each image. Flow of the feature extraction process is shown in Fig. 3.

Once all of the labelled training fruits images have gone through the *k*-NN classifier, a predictive model is generated where the trained *k*-NN is now ready to recognise unknown fruits. Given a testing image, the trained *k*-NN classifier will determine among the stored training images data, which one will have the shortest or closest distance to the input image. Based on that, the system will classify and assign the input image to its respective class. The value chosen for *k*=1 and the Euclidean distance function is used in calculating the distance between feature vector of input image and the feature vector of the training images. Fig. 4 shows the flow diagram for the recognition process.

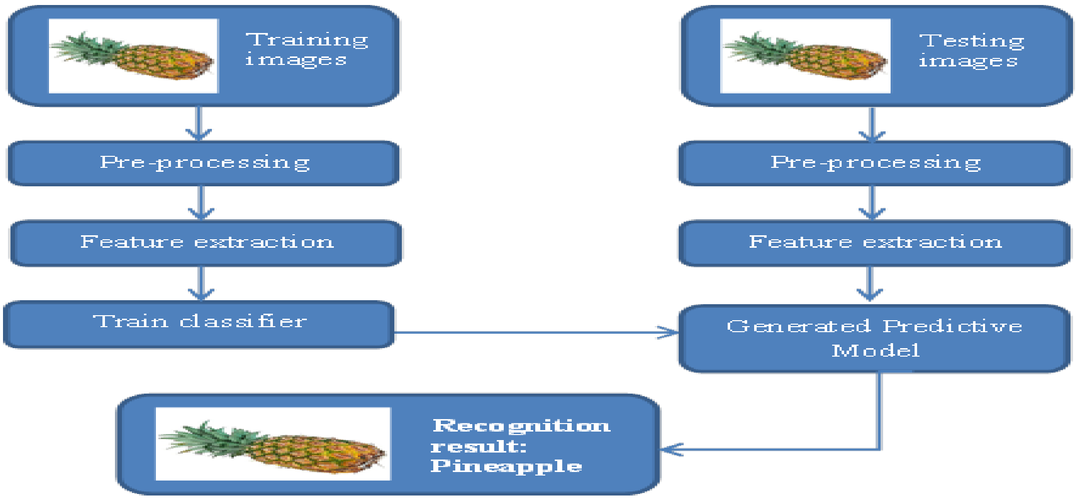

Fig. 2: Training and Testing Processes

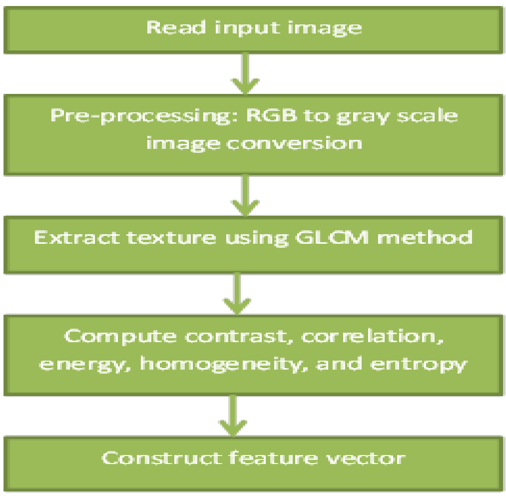

Fig. 3: Feature Extraction Process

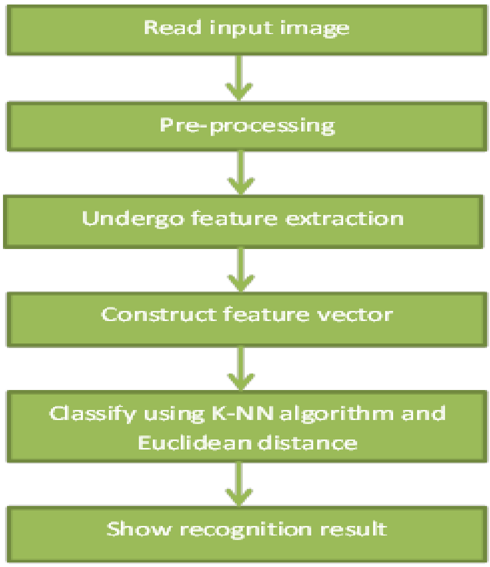

Fig. 4: Fruit Recognition Process

4. System Specification

The following hardware specification is used for this work; Intel ® Core ™ i3-5010U 2.10 GHz, 4GB Random Access Memory, and 64-bit Windows 10 operating system. MATLAB R2015a is the main software for development.

The Entity–Relationship diagram of the proposed fruits recognition system is shown in Fig. 5 below. The 'Image' is the entity which is represented by rectangle shape and has one attribute called imageID. The imageID acts as the primary key in this ERD. The 'Image' entity has a one-to-one relationship with the 'glcmValue' entity. The 'glcmValue' contained six attributes which are imageID, contrastVal, correVal, energyVal, entropyVal and homoVal. Besides that, the 'image' entity also has one-to-one relationship with the 'fruitDescription' entity. The five attributes that contained in 'fruitDescription' entity are imageID, comName, scienName, description and benefit.

Fig. 6 shows add or delete page of the fruits recognition system. For adding new training image, user will have to upload a new image and click on 'Add New Image' button to save the image automatically. If user wants to delete a particular image, user will only have to upload that image and click on the delete button, so the image will be deleted.

Fig. 7 shows the interface of recognition page. Recognition page interface consists of six buttons where each of them has its own functions. At the top part of the interface is the 'Browse' button that allows the user to browse the training image folder. After browsing the folder, the list of fruit categories will pop up in the list box on the left hand side. Then, user needs to click on 'Generate Training Image' button so that the system will undergo feature extraction for all of the training images.

The next button is 'Upload Image' button that allows the user to upload an image into the interface for recognition (testing). The uploaded image will be displayed in the middle of the interface.

At the bottom part, there are three buttons which are 'Recognise' button, 'Fruit Description' button and 'Back' button. Once user clicks on the 'Recognise' button, it will do the feature extraction and automatically the GLCM values that have been computed will be shown in the right hand side 'GLCM Method' box. The recognition result will appear in the text field named as 'Result'.

If the user clicks on the 'Fruit Description' button, the system will redirect user to the fruit description page as shown in Fig. 8. When user clicks on the 'Back' button, it will allow user to go back to the main page.

The 'Fruit Description' page will display the common name of the fruit, its scientific name, description about the fruit and its health benefits. If user wants to know the details on apple, user can click on the 'Apple' button and the apple's description will appear automatically. The same way is applied for other fruits. The 'Back' button will bring user back to the recognition page.

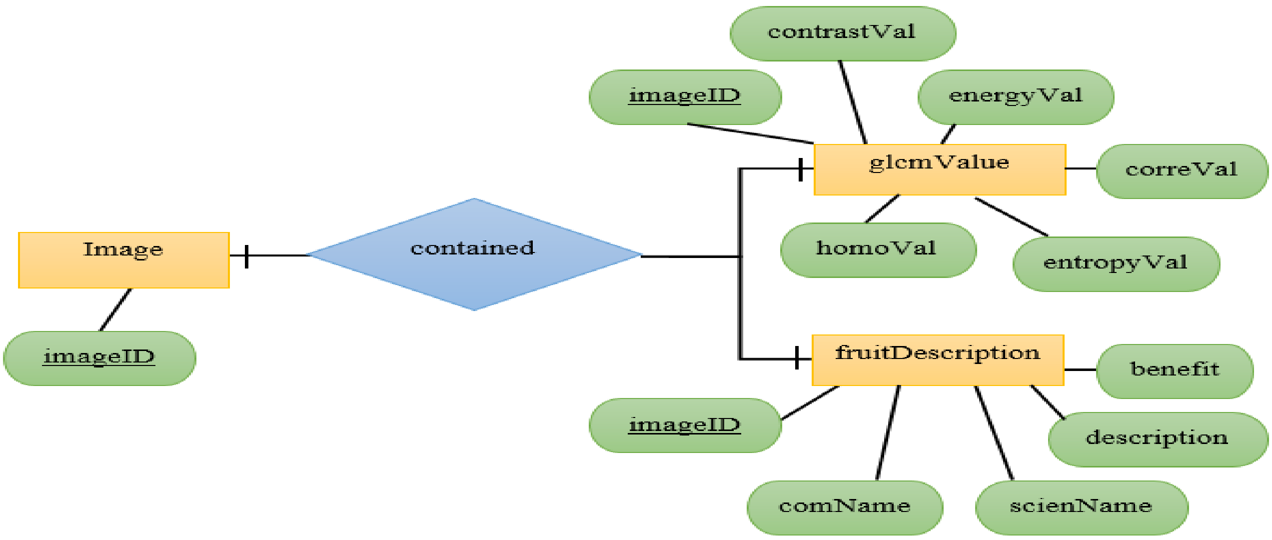

Fig. 5: Entity-relationship Diagram of the System

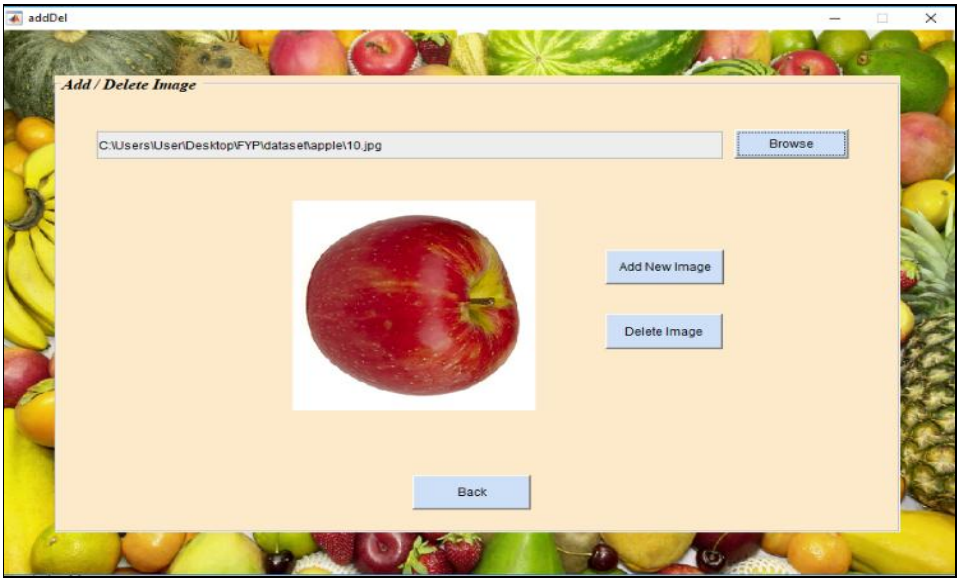

Fig. 6: Upload Training Image into Folder

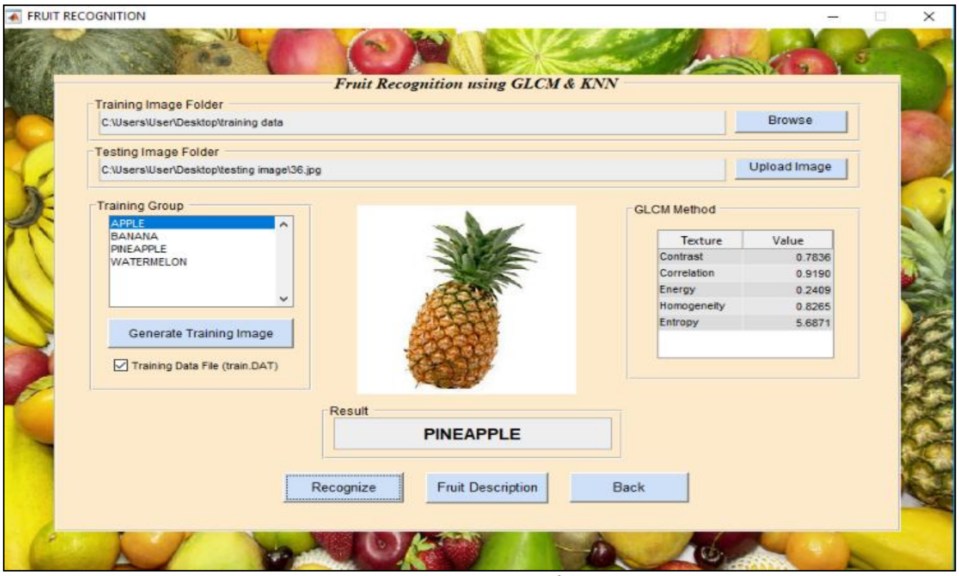

Fig. 7: Recognition Page of the System

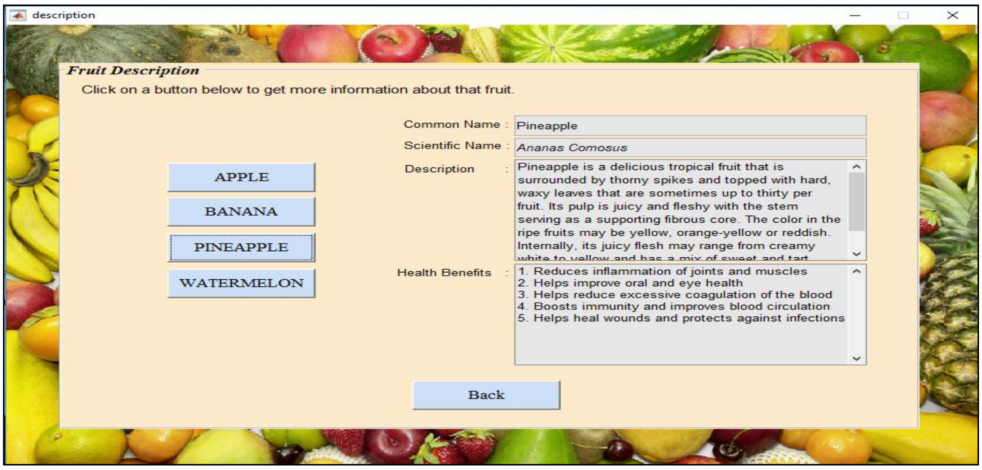

Fig. 8: Fruit Description Page of the System

5. Results and Discussions

Four categories of fruits are considered for evaluating the proposed framework which includes apple, banana, pineapple, and watermelon. Each of the categories has 13 images where the fruits are in different positions and orientations. In total, there are 52 fruit images being downloaded from the Internet. All of the images are in the same size, 256×256. The fruit dataset is shown in Fig. 9 below.

70% of the images are used for training (36 images) while 30% of the images are used for testing (16 images). 10-fold cross validation is used for validation. In 10-fold cross validation, the training set is divided into ten equal folders. Nine out of ten folders are used for training and the remaining is used for validating. The cross validation process is repeated ten times, with each of the folders are used exactly once as the validation data. In each fold, the accuracy performance is evaluated. The average of overall 10-folds accuracy is then computed.

As mentioned in Section 2, there are 14 texture features which can be extracted based on GLCM. Each of these texture features has different functionality and capability that would give different effect to the representation. However, utilising all features will result in higher computation, complexity, and storage. It is also not always the case where more features will result in better representation. Therefore, an experiment is conducted in order to investigate the effect of each feature for fruits representation. We tested on all 13 textural features except sum of squares feature as the equation could not be obtained during the time that the experiment is conducted. The accuracy obtained using different texture features has been recorded in the following Table 1.

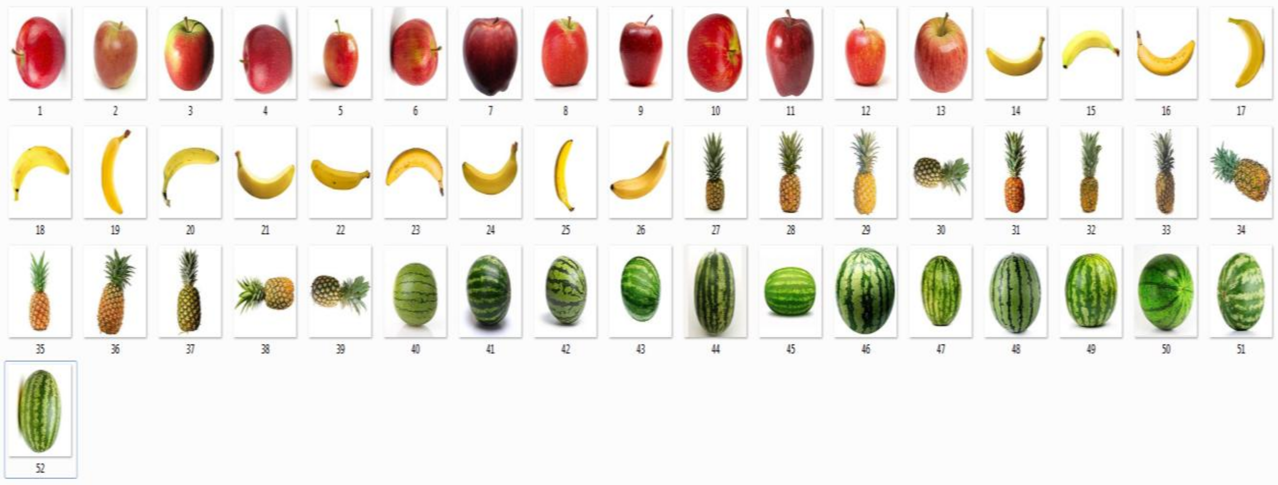

Fig. 9: Fruit Images

Table 1: Recognition Rate of Each Texture Features

Haralick Texture Features	Accuracy (%)
Sum Average	13
Variance	19
Difference Variance	19
Sum Variance	25
Difference Entropy	31
Sum Entropy	38
Information Measure of Correlation I	38
Information Measure of Correlation I	44
Contrast	50
Correlation	50
Entropy	56
Angular Second Moment (Energy)	63
Inverse Difference Moment Homogeneity)	69

From the result shown in Table 1, it can be observed that the accuracy obtained based on individual texture feature are quite low. The lowest accuracy is 13% which is computed from sum average feature. When using the inverse difference moment (homogeneity) feature, it gave 69% of accuracy where it is the highest percentage. It can be seen that the accuracy is not good enough if using only one feature where it is below than 70%. Thus, we did another investigation to observe on the possibility of improving the accuracy by fusing together several of the texture features.

Therefore, the second experiment is conducted which is to determine the possibility of best texture features combination. The experimental setting in terms of training and testing images is similar to the previous experiment. From the results obtained in Table 1, the first two highest features were taken and combined together to compute the accuracy. Then, the accuracy of the combined features is recorded. Through the same way, the experiment is continued by combining the next three best features up to five features. This experiment is stopped at five features because the combination of five features has achieved 100% accuracy. Table 2 shows the accuracy results when combining together several texture features.

It can be observed that the combination of five textural features able to produce the highest accuracy. Therefore, five texture features which are contrast, correlation, energy, homogeneity and entropy have been selected for this work.

Table 3 shows the summary of the average accuracy obtained for each type of fruit when testing the overall framework. It can be observed that the selected five texture features can represent the fruits information well and when combined with the *k*-NN classifier results in a fruit recognition system with very high overall accuracy.

Table 2: Recognition Accuracy of Combined Texture Features

Combination of Features	Accuracy (%)
Two features	26.4
Three features	54.5
Four features	70.5
Five features	100

Table 3: Confusion Matrix Table

Fruit	Accuracy (%)
Apple	100
Banana	100
Pineapple	100
Watermelon	100
Average	**100**

6. Conclusion and Future Research

Malaysia is well-known for its variety of fruits available in the country, either seasonal or non-seasonal fruits. Therefore, it is important for people to get to know more about fruits so that they can take advantage of all the benefits offered by each fruit.

This paper has contributed to a fruit recognition framework based on GLCM texture features for fruits representation and k-NN as the classifier model to predict the correct type of fruit given a fruit image as the input. Few experiments have been conducted to determine suitable combination of GLCM features. A fruit recognition system implementing the proposed framework has also been developed. Empirical study has shown that an accuracy rate of 100% is achieved for the proposed work.

With the development of the recognition system for fruits, users can recognise various fruits and obtain more information about the fruits just by using an image. Given an image of a fruit, the system is able to recognise its type as well as displaying few facts regarding the respective fruit such as its scientific name and the health benefits of the fruit.

For future work, we plan to expand the dataset so that more types of fruits can be recognised by the system. We also plan to extend the work to mobile version so that it can be used more widely.

Acknowledgement

This research is supported in part by Ministry of Higher Education (MoHE), Malaysia and Universiti Putra Malaysia (UPM).

References

[1] Ding C, Choi J, Tao D & Davis L (2016), Multi-directional multi-level dual-cross patterns for robust face recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 38(3), 518-531.

[2] Ding C & Tao D (2015), Robust face recognition via multimodal deep face representation. IEEE Transactions on Multimedia, 17(11), 2049-2058.

[3] Boles A & Rad P, Voice biometrics: Deep learning-based voiceprint authentication system. Proceedings of the 2017 12th Conference on System of Systems Engineering (SoSE), Waikoloa, Hawaii, USA, June 18-21, 2017, IEEE, 1-6.

[4] Kumar P, Saini R, Roy PP & Pal U (2018), A lexicon-free approach for 3D handwriting recognition using classifier combination. Pattern Recognition Letters, 103, 1-7.

[5] Kahou, Samira Ebrahimi, Xavier Bouthillier, Pascal Lamblin, Caglar Gulcehre, Vincent Michalski, Kishore Konda, Sébastien Jean et al. (2016), Emonets: Multimodal deep learning approaches for emotion recognition in video. Journal on Multimodal User Interfaces, 10(2), 99-111.

[6] Escalera S, Athitsos V & Guyon I, Challenges in multi-modal gesture recognition. Gesture Recognition, Springer, Cham, 2017, 1-60.

[7] Llano EG, Vázquez MSG, Vargas JMC, Fuentes LMZ & Acosta AAR (2018), Optimized robust multi-sensor scheme for simultaneous video and image iris recognition. Pattern Recognition Letters, 101, 44-51.

[8] Seng WC & Mirisaee SH, A new method for fruits recognition system. Proceedings of the 2009 International Conference on Electrical Engineering and Informatics, Selangor, Malaysia, August 5-7, 2009, IEEE, 130-134.

[9] Ebert C & Louridas P (2016), Machine learning. IEEE Software, 33(5), 110-115.

[10] Muhtaseb A, Sarahneh S & Tamimi H, Fruit / vegetable recognition. Proceedings of the 2012 Student Innovation Conference, Hebron, Palestine, June, 2012.

[11] Mohana SH & Prabhakar CJ (2014), A novel technique for grading of dates using shape and texture. An International Journal (MLAIJ), 1(2), 15-29.

[12] Nasirahmadi A & Ashtiani SHM (2017), Bag-of-Feature model for sweet and bitter almond classification. Biosystems Engineering, 156, 51-60.

[13] Mohanaiah P, Sathyanarayana P & Gurukumar L (2013), Image texture feature extraction using GLCM approach. International Journal of Scientific and Research Publications, 3(5), 1-5.

[14] Semary NA, Tharwat A, Elhariri E & Hassanien AE, Fruit-based tomato grading system using features fusion and support vector machine. Intelligent Systems' 2014, 2015, Springer, Cham, 401-410.