Fruit Recognition Using Surface and Geometric Information

Joel C. De Goma[1], Cyrus Arlan M. Quilas[1], Maurice Albert B. Valerio[1], Jon Jake P. Young[1] and Zaliman Sauli[2]
[1]*School of Information Technology, Mapúa University, Makati 333 Sen. Gil Puyat Ave., Makati City 1200, Philippines.*
[2]*School of Microelectronic Engineering, Universiti Malaysia Perlis, Pauh Putra Campus, 02600 Arau, Perlis, Malaysia.*
jcdegoma@mapua.edu.ph

***Abstract*—One of the interesting topics in image processing and computer vision is Fruit Recognition. The computer vision strategies used to recognise fruits rely on four basic features which are colour, texture, size and shape. In fruit recognition, unrecognised fruit images are caused by different factors. These factors are different illuminations, specular reflections, and different poses of each fruit, variability on the number of elements, and cropping or occlusions. This paper proposes and aims an efficient and effective way to recognise fruits regardless of the said factors by combining the four basic features of the fruit. Fruit recognition involves different processes which are pre-processing, feature extraction, recognition and testing. The recognition is done using the K-Nearest Neighbor based on statistical values of the colour moments, Gray Level Co-occurrence Matrix (GLCM) features, area by pixels for the size and shape roundness. The fruit images comprised of 2633 fruit images from 15 different kinds of fruits. The authors tested different classifiers which are KNN, Naïve Bayes, Decision Tree, and bagging to know what best fits for the images. After testing the classifiers based on the 2633 images, results showed that KNN outperformed the other classifiers. The result showed that combining all the features namely colour, texture, size and shape, the overall recognition rate for all classifiers has increased and it has shown the best output.**

***Index Terms*—Fruit Recognition; Co-Occurrence Features; Pre-Processing; Feature Extraction; K- Nearest Neighbor.**

I. INTRODUCTION

The area of digital image processing signifies to processing digital images using a digital computer. Vision is the most advanced of human senses. Thus, the image has a significant role in human discernment. The difference between human and machine perception is that machines cover almost the entire electromagnetic (EM) spectrum ranging from gamma to radio waves while humans are limited to the visual band. Computer vision is one of the areas where human vision is emulated using computers to analyse the visual inputs for learning and decision making for decision making and information erudition [1]. Computer Vision (CV) is the process of applying a range of technologies and methods to provide imaging-based automatic inspection, process control and robot guidance in industrial application [2]. It has found application in areas such as industrial process control, medical diagnostics, aerial surveillance, remote sensing, robotics, optical character recognition, voice recognition, face recognition, and more. Along with these applications of automation and fabrication, it has also spread to the agriculture products and one of them is fruit recognition.

The computer vision is facing a great challenge in making its recognition system as effective as human level recognition for many various applications in the long term.

One of the applications of computer vision currently being utilised for fruit recognition which is based on four basic features which are colour, shape, intensity and texture that is used to analyse the fruit characteristics [3].

Shape and colour based analysis methods are one of the utmost prevalent methods used for fruit image analysis. A disadvantage is that some fruits have the same shape and colour. Thus, utilising shape, colour and size analysis methods is less effective in identifying fruit images [4].

Currently, the cashiers at supermarkets are facing the continual daily task of recognising various types of fruits and vegetables to determine its prices. This is currently being done by using barcodes which requires specific codes for each type of fruits and vegetables. However, the cashiers are required to memorise all these codes which may be troublesome and may cost error. In addition, the cashiers are aided with barcode booklets for price identification, and this will consume time as frequent flipping is required for price referencing [5]. Hence, a system adapting to the requirement for fruits identification in supermarkets based on computer vision based on texture, size, colour and shape is required [5]. The system must be able to identify the given image of the fruit and provide the list of matching fruits that can be utilised by customers at supermarkets for labelling and prices based on their own selection of products using automatic fruit recognition based on computer vision. With the existing use of computers to analyse images of fruits, many applications have been developed. However, there are still gaps to be filled. A different agricultural object makes it complicated to adapt to the current industrial algorithms to the agricultural domain [3].

The proposed study fills these gaps by continuing the work of Arivazhagan, et al. [3] and following the recommendation. The previous work shows that the experimental results were 86% using colour and texture features. The study also shows that combining features results into an increase in recognition rate because when only using colour features or texture features independently, it shows that the results are only 45.49% and 70.86% respectively. To further increase the recognition rate, it is necessary to add more features like size and shape and also to increase the number of images in the feature database.

II. MATERIAL AND METHODS

This research focuses on image processing of fruits using different feature extraction techniques. Figure 1 illustrates the conceptual framework and the process flow involved in this research. To support this research, the authors will be using the Supermarket Produce Data Set; it is composed of 15 different types of fruit with a total of 2,633 images. The image database is divided into two parts which are used for training and testing. Seventy percent of the image database is used as training sets, and 30% are used as testing sets. Table 1 shows how many images are there in a training set and a testing set for each type of fruit.

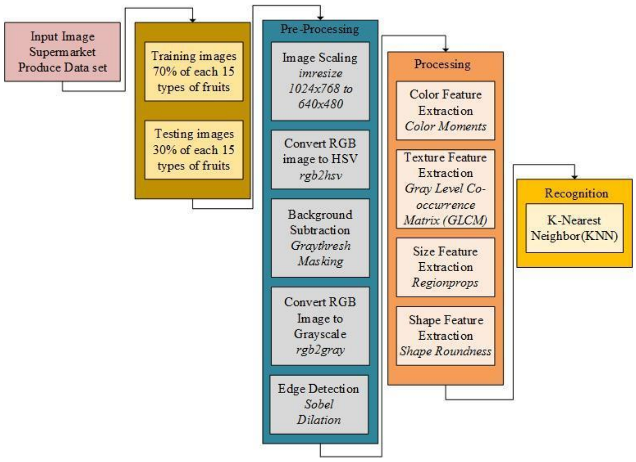

Figure 1: Conceptual Framework

Table 1
Training and Testing Sets

Fruit Class	Number of Images	Training Set 70%	Testing Set 30%
Plum	264	185	79
Agata Potato	201	141	60
Asterix Potato	182	128	54
Cashew	210	147	63
Onion	75	53	22
Orange	103	73	30
Taiti Lime	106	75	31
Kiwi	171	120	51
Fuji Apple	212	149	63
Granny-Smith Apple	155	109	46
Watermelon	192	135	57
Honeydew Melon	145	102	43
Nectarine	247	173	74
Williams Pear	159	112	47
Diamond Peach	211	148	63
Total	2,633	1,850	783

A. *Data Gathering*

The dataset that was used in this research is called the *Supermarket Produce* data set and was retrieved from the two studies of Rocha, *et al.* [5]. Several studies had also used this dataset like the study of Arivazhagan, *et al.* entitled "Fruit Recognition using Color and Texture Features" [3] and the study of Chaw and Mokji entitled "Produce Recognition System Using Data Mining Algorithm" [7]. *Supermarket Produce* dataset is one of a few well-recognised image data sets accessible for the testing algorithm based on image categorisation and retrieval. ALOI and Caltech are two examples of such datasets [5]. It has 15 different categories which are Plums, Agata Potato, Cashew, Kiwi, Fuji Apple, Granny-Smith Apple, Watermelon, Honeydew Melon, Nectarine, William Pear, Diamond Peach, Asterix Potato, Onion, Orange, and Tahiti Lime; with a total of 2,633 images [5]. They used a Canon PowerShot P1 camera, at a resolution of 1024x768 pixels. They down-sampled it to 640x480 pixels and used a white background. Entire images are stored in RGB colour space with 8 bits per pixel in JPEG format. Images are collected at various times of the day and diverse days for a particular image. This is due to create a realistic and precise image based on variation. Daylight exposure varies the illumination, and it is not artificially tampered. It also comprises differences in pose and some elements within an image. Some are in a repository or plastic bag which adds causes peculiar reflections to the analysed image. Shadows and cropping/occlusions are also present to make the data set more realistic [5]. Figure 2 illustrates the data gathering procedure. For this work, the authors used a smartphone iPhone 5s with flash capabilities to have adequate lighting source and a white table for white background. The white background is set to eliminate external colour noise. The distance between the fruits and the camera was adjusted from 0.5 m to 1m depending on the fruit sample and its overall dimension. The images were set to 640x480 pixels. Images are collected at various times of the day to create a realistic and precise image based on variation. After gathering all the fruit images, the image is transferred and saved into a laptop. All images were stored in RGB colour space in JPEG format. Next, the process flow shown in Figure 1 is applied to all captured image for further processing.

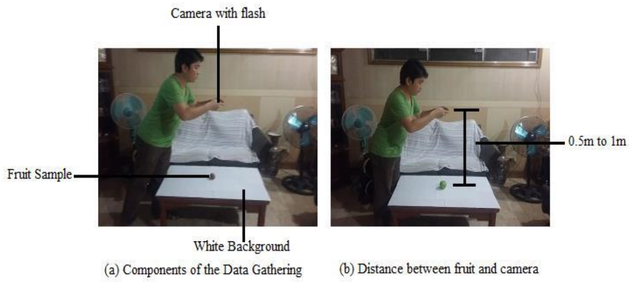

Figure 2: Data gathering illustration

III. RESULTS AND DISCUSSIONS

Based on Figure 3, when K is lower, the higher is the accuracy. The researchers chose K = 10 as a best optimal K-value because the K-value must have a good result and at the same time have a high accuracy with a better number of neighbours to recall so that the classifier has a basis to search more neighbours than K = 1 which has the highest accuracy.

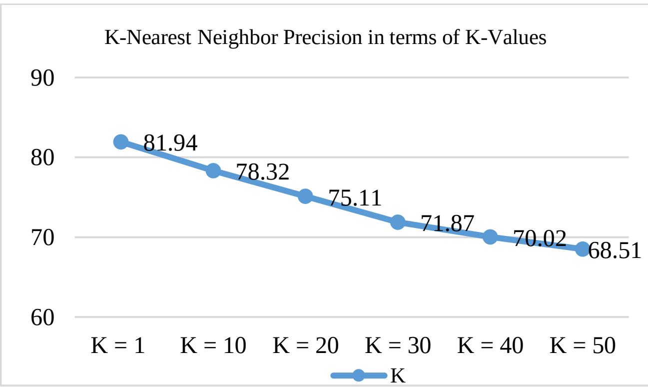

Figure 3: K-Nearest Neighbor Precision regarding K-Values

Figure 4 illustrates the fruit recognition accuracy based on features. The results are presented regarding colour, texture, colour and texture, a combination of colour, texture, size and shape. Based on the results, the combined colour, texture, size, and shape features showed the highest recognition rate among the combinations based on the recognition done using KNN.

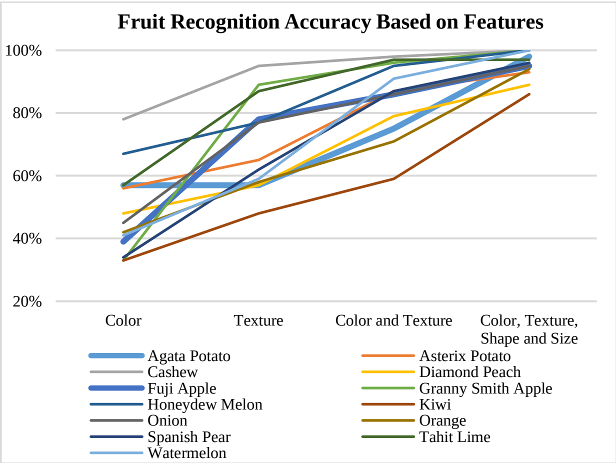

Figure 4: Fruit Recognition Accuracy Based on Features

Table 2 shows the statistical values of the classifiers. Figure 5 illustrates the classifiers recognition rate. According to the Table 2 and Figure 5, KNN is still the best fit for the study regarding the majority of the features, while the Naïve Bayes is close to it. The Naïve Bayes classifier is based on a simple and intuitive concept. Naïve Bayes algorithm has an upper edge over another complex algorithm as it utilises variables contained in the data sample, by analysing them individually, independent of each other[8]. Bagging is also tested in this study; it is a meta-algorithm designed to find, generate, or select a heuristic that may provide a good solution to an optimisation problem, according to the graph. Bagging gives a promising value that can also give good results in all features. J48, on the other hand, resulted in a low accuracy rate. According to other studies, a J48 decision tree is a predictive machine-learning model that chooses the target value (dependent variable) of a fresh sample based on various feature values of the available data. The enclosed nodes of a decision tree identify the various features, whereas the branches between the nodes inform the conceivable values of the stated features which may be in the analysed sample, and the terminal nodes evaluate the final value of classification, thus making J48 is not suitable for this research[8].

Table 2
Statistical Values of Classifiers

Classifiers	Properties	
K-Nearest Neighbor	Accuracy	81.94%
	Kappa Statistic	0.8052
	Mean Absolute Error	0.0247
	Relative Absolute Error	19.98%
Naïve Bayes	Accuracy	61.84%
	Kappa Statistic	0.5888
	Mean Absolute Error	0.0515
	Relative Absolute Error	41.65%
J-48	Accuracy	81.45%
	Kappa Statistic	0.8
	Mean Absolute Error	0.0279
	Relative Absolute Error	22.54%
Bagging	Accuracy	78.4%
	Kappa Statistic	0.8373
	Mean Absolute Error	0.0358
	Relative Absolute Error	29.95%

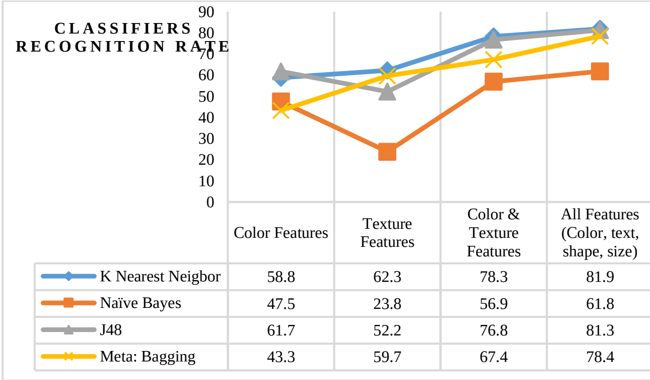

Figure 5: Classifiers recognition rate

This paper aims to increase the accuracy of the system by applying shape and size feature extraction from the previous study. The previous study only applied colour and texture feature extraction, and they recommended to add shape and size features for further improvements. After undergoing many experiments and trial and errors, results showed that combining the shape and size of the texture and colour feature extraction increased the percentage accuracy of the system.

The results of colour feature only yield a very low accuracy. Most of the fruits like Honeydew Melon, Tahiti Lime, Kiwi, and Spanish Pear only got below 40% of the accuracy rate. Colour features only extract the values of the colour moments from the HSV Color Space. Most of the fruits have the same colour like green and yellow that concludes why the colour features of most of the fruits are very low in accuracy.

The results of texture feature only yield a higher result than colour features, because unlike the colour feature where the values depend on the colour values of the fruits in HSV colour space, and it is highly to be common to one another. Texture feature only extracts the values from the Gray Level Image and getting the values of the contrast, energy, homogeneity, cluster shade and cluster prominence. The Figure 5 shows that the texture of every fruit yields higher than their colour feature results, because of their uniquely structured textures, and not all of them have a typical texture, some are smooth like watermelon, some are rough like Kiwi, and some have ragged surfaces like orange.

Combining the colour feature and texture feature yields a more significant result for identifying the tested fruits. According to the Figure 5 shows the combination of colour and texture features of all the fruit increased, rather than using one feature at a time. It is because the system can verify two features at a time, the more features that are extracted, the better the recognition rate. Some of the results like the Agata Potato, from the percentage of 57% on colour feature only and 57% on texture feature only, it increased the accuracy by 18%. For the smallest fruit Kiwi, the highest result in texture feature only is 48%. After combining both features, it increased by 11%.

Finally, by combining all the features namely colour, texture, size and shape, the overall recognition rate for all classifiers has increased, and it has shown the best output.

IV. Conclusion

In this study, an effective method to identify fruits was done by combining four basic features of the fruit. Fruit recognition involved different processes which are pre-processing, feature extraction, recognition and testing. The K-Nearest Neighbor based on statistical values of the colour moments, Gray Level Co-occurrence Matrix (GLCM) features, area by pixels for the size and shape roundness was utilised for the recognition purpose. Four different classifiers were tested, and key findings showed that KNN outperformed Naïve Bayes, Decision Tree, and Bagging to identify the best fits for the images. The result showed that combining all the features namely colour, texture, size and shape, the overall recognition rate for all classifiers has increased and it has shown the best output.

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