

MATLAB-Based Precision Image Analysis for Fruit Sorting

Farid Eltom. A. E^{1,3*}, Udoka Joseph Tochi², W. Dongwei¹, B. O. Oyefeso², Oluwaseun Kadiri¹, Haroun Mohammed^{1,3}

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ABSTRACT

Fruits are extremely fundamental in our everyday diet. The palatable fruits are harvested, sorted, and packed for conveyance to the consumers. It needs a large number of expert resources and a long time to sort and grade the fruits from the agricultural field to the fruit markets. Automation in the agricultural field and fruit markets is a must to reduce the time as well as the dependency on the manual resource. Thus, the objective of this project is to fully automate the sorting process of handling fruits. The proposed method used an image acquisition system (camera), which acquires the images of the various selected fruits (Apple, Onion, Banana, Pepper and Tomato) used for the training data. The textural and colour features of the selected fruits were extracted and then, processed using the MATLAB software with Support vector machine (SVM) algorithm as the classifier. The fruit recognition system classified the input fruit sample by determining the similarities between the colour and gray level co-occurrence matrix values of the inputted fruits samples and the values obtained from the training datasets. The proposed method is accurate and flexible. Also, a graphical user interface was developed to be used independently of the software, the recognition rate of the system had an average accuracy of 97%.

1. Introduction

Increasingly Fruits are an inevitable element of the human food intake system, and they supply us with the needed nutriment, minerals, and antioxidants to sustain our health (Susovan et al., 2020). Although these fruits have varying preferences, their visual features are mostly similar hence manual grading is cumbersome, lengthy and consumes a lot of human resource as fruits are moved to the market lacking uniformity (Jhuria et al., 2013). Market and Agricultural automation are necessary to minimize time and labour dependency and the process of categorizing fruits and vegetables is just one of the many steps towards achieving an automated efficient system (Zawbaa et al., 2014; Liang, Y, 2017). Classification of fruits in automatic ways based on visual attributes is not an easy one and has been solved by the image processing techniques, where attributes like color, shape, texture, and size are identified and used in the classification of the fruits (Mohanaiah et al., 2013; & Mirisae, 2009).

¹Farid Eltom. A. E

Yellow River Delta Intelligent Agricultural Equipment Industry Academy, Dongying, China @ Africa City of Technology, Khartoum, 11111, Sudan, e-mail address: farideltoum@gmail.com.

²Udoka Joseph Tochi

University of Ibadan, Faculty of Technology, Department of Agricultural and Environmental Engineering, Nigeria, e-mail address: kzizitech@gmail.com

³W. Dongwei

Yellow River Delta Intelligent Agricultural Equipment Industry Academy, Dongying, China e-mail address: yarid@yrdia.cn

⁴B. O. Oyefeso

University of Ibadan, Faculty of Technology, Department of Agricultural and Environmental Engineering, Nigeria

e-mail address: aokadiri@logsstate.gov.ng

⁵Oluwaseun Kadiri: Yellow River Delta Intelligent Agricultural Equipment Industry Academy

⁶Haroun Mohammed : Yellow River Delta Intelligent Agricultural Equipment Industry Academy

These systems are also helpful to visually impaired people and consumers who do not know a lot about fruit varieties as they can also identify their varieties in real-time (Ukwuoma et al., 2022). Digital image processing and computer vision applications have been a common place in robotics, medical diagnostics, security, industry automation, and the field of human-computer interaction, providing an opportunity to make a complex visual analysis of two-dimensional data and even a three-dimensional one, in order to determine structural and textural attributes beyond human view (Burger & Burge, 2009; Solomon & Breckon, 2011).

The usage of computer hardware (CCD cameras, complex software applications such as MATLAB) makes the collection of optimal images, as well as their processing and extraction of features, related to objects in different environmental circumstances possible (Gonzalez et al., 2004). Image processing may be considerably efficient in the agricultural sector where it could contribute positively by minimizing the workforce and making the operations to run on time (Raji & Alamutu, 2005). The main goal of this study is to create a fully automated system that would sort the fruit based on the method of image processing, and this system can save labor and enhance performance in the processes of sorting and grading (Sabzi et al., 2018). This paper shows the progress of a fruit recognition algorithm prototype that recognizes a few of the most consumable fruits in Nigeria (apple, banana, tomato, pepper, and onion) with the potential of applying it to more fruits by extending the dataset. The mechanism adds to the development of intelligent farming systems to efficiently sort out and quality-checks of fruits (Kabir, M. S. N., 2023; Zhao et al., 2005).

In the past few years, multiple methods of image analysis have been used to evaluate the fruit pictures based on recognition and classification creating an active dynamic research field which has various algorithms to perform the image analysis. The researchers have been using different approaches that suit definite characteristics of fruits. One of them is to pay attention to the features of shape, size, and color. Seng and Mirisae (2009) came up with a system based on these attributes and attained 90 per cent accuracy although it was not versatile across different fruits. Kadir Abdul et al (2011) modified this using texture and vein features to incorporate PNN classifier with the Flavia dataset achieving an accuracy of 93.75 percent. An improvement in accuracy was achieved by Kim et al. (2011) to 90 percent through a blending of intensity-based techniques with the features of color, shape, and size. Surveying the work of Mustafa et al. (2011), a sorting system of several fruits was developed, which with morphological and color information achieved an efficiency of 79-90%. Hasan et al. (2014) portrays fuzzy logic-based mango grading as accurate as 77.78 percent but Ninawe and Pandey (2014) have provided KNN-based grading using multi-feature and this approach failed to handle the variability. Zawbaa et al. (2014) employed KNN and SVM based on shape and color, and their accuracy, in turn, was problematic, whereas Zhang et al. (2016) managed to attain 89% accuracy using neural networks but depending on the type of fruit. Sabzi et al. (2018) used neural networks to analyze varieties of oranges and found inefficiency.

More recent developments in machine vision-based fruit sorting have seen a dramatic transition towards deep learning methods, new studies have reported stunning classification performance (Zhou et al., 2023). In a similar way, it has employed the lightweight convolutional neural networks that can automatically classify fruits such as olives into maturity levels of the fruits with a high accuracy and using a small amount of computational power (Saedi et al., 2024). They are interchangeable with the conventional techniques based on SVM to detect the features in MATLAB used in tomato and other processing systems of produce grading (Bhadouria, 2023). On this, we use the HSV color space and GLCM texture feature coupled with SVM to better sort desired fruits in Nigeria. The past research indicates that the accuracy of classification of fruits depends on the size of the dataset, conditions, and the methods. Seng and Mirisae (2009) hit 90% on small datasets that do not characterize texture, whereas Zhang et al. (2016) hit 89% with neural networks, influenced by dependencies of fruits and overfitting. In controlled conditions with noise reduction, Aibinu et al. (2011) achieved 99.1% generalizability was limited. According to recent reviews, such variables as dataset variation and quality of images influence the performance of SVM, which proves our HSV-GLCM as the method of effective feature extraction

The approaches relying on texture comprise Zhao et al. (2005) with the accuracy of 90% to detect apples, Baltazar et al. (2008) who used neural networks to recognize tomatoes, Aibinu et al. (2011) who established the accuracy of 99.1 using ANN, Li and Fieguth (2012) to enhance texture classification, and Nanaa Kutiba et al. (2014) with the accuracy of 96.26 regarding mangoes.

2. Methodology

Plain Image processing theory is the basis of performing the analysis of the fruit images and digital image processing is one of their central parts. Image is described as a 2D array of pixels that organized or sorted in rows and columns in which they are the representation of a brightness pattern of the image and it can be $f(x,y)$ where x,y are the spatial coordinates and the brightness at each position will be the intensity of brightness (Solomon and Breckon, 2011; Gonzalez et al., 2004). An image in the digital form is a discretized representation of this function, the projection of the latter in the form of a 2-dimensional integer array, where each element (a pixel) contains a gray level value, the fundamental unit of data of a specific resolution and quantization level (Fernando et al, 2010; Solomon and Breckon, 2011). It is presented as a combination in the form of a table where every element (pixel) occupies a definite position and has its value. The fundamental measurements of images involve spatial resolution, pixel bit depth and color that defines the data that is retrieved of the original scene. Greater results in such measures increase the representation of detail. The number of pixels in row (R) and columns (C) such as 640 x 480 defines spatial resolution, which expresses sampling of an image (Solomon and Breckon, 2011). The temporal resolution applicable to a video is in frames per second (fps) and, at 25-30 fps, useful to surveillance (Solomon and Breckon, 2011).

The suggested system uses MATLAB to process and acquire images, convert RGB images to HSV space to analyze the colors effectively with changing light conditions, which can be analyzed by the latest prototypes of grading (Bhadouria, 2023). GLCM was used to extract texture characteristics such as contrast, energy and homogeneity and the textures were classified with SVM. This combination model is in accordance with the current advances in on-farm AI that integrate ANN and SVM to estimate the volume of apples and mangoes (Zhou et al., 2023). In case of olive-like sorting, a dual path network may be an extension of our model, whereas SVM can also be used in our dataset size (Saedi et al., 2024).

The number of bit indicates the potential intensity/ color-enabled per pixel; binary (2-bit), grayscale (8-bit), and color (24-bit), which influences dynamic range (Solomon and Breckon, 2011). The smallest elements of an image are called pixels, and the amount of light intensity in a specific pixel is assigned then in the 0-255 range of values in 8-bit grayscale representation (e.g., pixel values equal 0,1,2,3 in intensity: 0-255) (Solomon and Breckon, 2011). The quantity of pixels is obtained by multiplying the columns (N_c) by rows (N_r): $T_p = N_r \times N_c$ (e.g., $T_p = 3 \times 3 =$ The colour depth is dependent on bits per pixel (BPP) the number of colors can be calculated as 2 to the power of BPP, i.e., 2 colours at 1 bit and 4 colours at 2-bit formula 1-2 and (Figure 1).

$$(1) T_p = N_r \times N_c$$

Where,

T_p = Total number of pixels

N_r = Number of rows

N_c = Number of columns

Or : The number of (x, y) co-ordinates pairs make up the total number of pixels

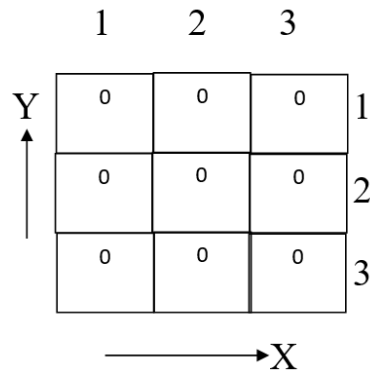


Figure 1: Pixel Representation

Zero (0) indicates the absence of light (dark or black colour).

$$(2) T_p = N_r \times N_c = 3 \times 3 = 9 \text{ pixels}$$

This means that the image would be formed with 9 pixels, and the image would have a dimension of 3 rows and 3 columns and most importantly the image would be black in color. Given that the number of different colours depend on the number of bits per pixel. Table 1 shows some of the bits and their colour.

Table 1. Different bits per pixel and the amount of colour they contain

Bits Per Pixel	Number of colours
2 bpp	4 colours
4 bpp	16 colours
8 bpp	64 colours
16 bpp	65536 colours
24 bpp	16.7 million colours
32 bpp	4294 million colours

2.1. Colour Representation/ Spaces

In Colour images are represented by a number of different systems, the dominant systems being RGB (additive), CMYK (subtractive), HSV and CIELAB colour representations.

a. RGB Colour Space

RGB colours are created by combining red, green and blue into colour, which is considered as a basic model of computer graphics because of its colour displaying purposes. In this additive system, the desired hue has to be made up of primary colours.

b. *CIE Lab (CIELAB) Colour Space

All perceivable colours can be measured in CIELAB by three dimensions, L^* (black = 0, diffuse white = 100) the lightness dimension, the greeny-red opposition a^* (negative = green, positive = magenta), and the bluey-yellow opposition b^* (negative = blue, positive = yellow). The asterisk (*) differentiates L , a^* , and b^* with that of Hunter describing the differences in visual colour measures.

3.2 Conversion of Colour Space

This is the process of translating a colour in one space in to another one, normally the translation of an image (e.g. RGB) to a second space, to be as 'similar to as it can be', which needs the value of RGB to perform efficiently.

2.2. Image Coord List System

Sampling and quantization provide a matrix of real numbers; the vertical coordinate system is just flipped in image processing. The starting point is (0, 0) at the top left and x has the range of 0 to M-1 and y with 0 to N-1 in an M N image (Gonzalez et al., 2004).

2.3. Images in the form of Matrices

Digital image is a real-valued function of a finite lattice subset which is normally represented in the form of a matrix where the elements of the matrix represent intensity or colour at a specified position (Gonzalez et al., 2004) (Figure 2).

$$\begin{bmatrix} A_{0,0} & A_{0,1} & A_{0,2} & \dots & \dots & A_{0,N-1} \\ A_{1,0} & A_{1,1} & A_{1,2} & \dots & \dots & A_{1,N-1} \\ \vdots & \vdots & \vdots & \ddots & & \vdots \\ \vdots & \vdots & \vdots & & \ddots & \vdots \\ \vdots & \vdots & \vdots & & & \vdots \\ A_{M-1,0} & A_{M-1,1} & A_{M-1,2} & \dots & \dots & A_{M-1,N-1} \end{bmatrix}$$

Figure 2. The matrix representation of images The data is defined as a two dimensional array, each element of which defines the intensity or colour at a particular point. The notation is that of a matrix, f (x, y) which has x and y being the spatial coordinates, and the brightness at a particular position represented by a value 0-255 in an 8-bit grayscale system.

The materials and software used in carrying this project work are presented in Table 2. All the details are gotten from the market survey that was carried out during the project execution. This was the purpose of his project in which it was able to characterize the dataset of designated fruits that it was trained to label. This study analyzed Apple, Banana, Tomato, Pepper, and Onion by using the Gray Level Co-occurrence Matrix (GLCM) approach, and the details of the protocol followed in this process are mentioned in the chapter, with a step-by-step description of the research procedure described in Figure 3.

Table 2. Materials Selection Quotation

S/N	Material/Tools	Description	Quantity	Unit (₦)	Price	Total (₦)	Price
1.	Camera Selection	-	1	1,900		2,000	
2.	Programmable Logic Controller	-	1	10,200		11,500	
3.	MATLAB software	Version R2014	1	-		-	
4.	PC	Core i3, CPU @1.70Ghz, 4GB RAM	1	-		-	

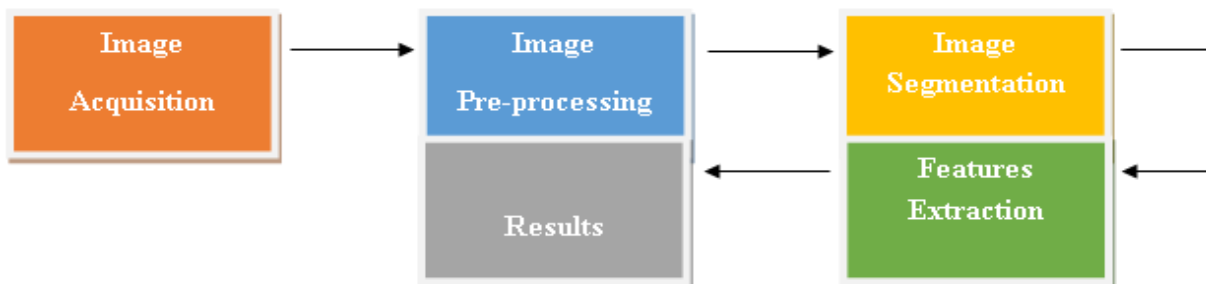


Figure 2. Image Processing Techniques

2.4. Image Acquisition

Pictures of apples, bananas, tomatoes, peppers and onion were captured via CCD sensor camera under sunlight so as to provide harmonious lighting. The fruits were placed in a conveyor belt and photographed at the most optimum distance where its images had high quality of no noise with little shadows. Digital camera performed the switching of images automatically; there was no longer a way which the process was done by hands. The pictures were saved in JPG files and were plugged into a computer that was to analyse the images. Background interference and noise were removed in preprocessing window in Adobe Photoshop after which segmentation was carried out in MATLAB color threshold algorithm which converted the RGB images to HSV and then binary images.

The analysis was conducted on the basis of shape features (the area, perimeter and roundness were determined with the help of the region properties), and the Grey-Level Co-occurrence Matrix (GLCM) was used to carry out testing of the texture. The principal features of GLCM were calculated to include contrast, energy, homogeneity, and correlation to give a platform of grouping the fruits based on the patterns of their surface. This method also brought accurate identification of the fruits since it utilizes both the geometrical and the textural characteristics to carry out a powerful analysis.

Local pixel variation is contrast, which is 0 with constant images and is computed as formula 3. Energy is the indicator of uniformity of pixel pairs between 0-1 (1 in the case of constant images) and is calculated as formula 4. A reciprocal difference moment, homogeneity, is defined as 0 to 1 (1 being all identical elements) and is inversely proportional to contrast, which is defined as formula 5. The correlation as the measure of linear dependencies between gray-levels is a value between -1 and +1 calculated as formula 6 and 7 (Mohanaiah et al., 2013). This direct solution combines color and texture analysis to provide a powerful and computationally inexpensive fruit classification implementation that can be used in automation of agriculture.

$$(3) \quad \textit{Perimeter} = \sum (\sqrt{\sum \delta^2})$$

Obtain the area calculation corresponding to label 'k' Area = stats (k). Area,

Compute the roundness metric.

$$(4) \quad \textit{Metric} = \frac{4\pi \times \textit{Area}}{\textit{Perimeter}^2}$$

$$(5) \quad \textit{Contrast} = \sum_{i,j=0}^{N=1} C(i,j)(i,j)^2$$

$$(6) \quad \textit{Energy} = \sum_{i,j=0}^{N=1} C(i,j)^2$$

$$(7) \quad \textit{Correlation} = \sum_{i,j=0}^{N=1} \frac{\{i \times j\} \times C(i,j) - \{\mu_x - \mu_y\}}{\sigma_x - \sigma_y}$$

2.5. Program Development

Based on the Gray Level Co-occurrence Matrix (GLCM) method, an algorithm was developed using the Matrix Laboratory (MATLAB) in order to analyse the images. The GLCM algorithm helped to extract the textural features of the images. This process was done automatically using specific functions in MATLAB that has been embedded in the software for such purpose. Each of the textural features of the image, was extracted and exported to create the training and test sets to be used as a learning parameter for the fruit recognition algorithm. A code was written for the fruit samples; the textural features were extracted and then compared with the samples already used to train the program.

3. Results

4.1 Dataset for training

The datasets comprising 5 different categories: Apple Braeburn, Apple Granny, Banana, Pepper Green, Pepper Red, Tomato as shown in Plate 1; totaling 1,113 images are used for experimental purpose.

Table 3. List of Images in Database

S. No.	Fruits	Total Number of Fruit Images	Number of Fruit Images used for	
			Training	Testing
1.	Apple (Braeburn and Granny Smith)	200	160	40
2.	Banana	100	75	25
3.	Onion	140	110	30
4.	Pepper (Red and Green)	270	230	40
5.	Tomato	410	360	50

These fruit images are divided into training and testing set, where 70% of the fruit images from each group are used to train the system and the remaining images served as the testing set. The number of images used for training and classification for each type of fruits is shown in Table 3. All of the images were stored in RGB colour space at 8 bits per channel. The images were gathered at various times of the day and in different days for the same category. These features increase the data set variability and represent a more realistic scenario (Figure 4).



Figure 4. Plate 1: Fruits used for Classification

3.2. Region of Interest Extraction Algorithm

- The equation of image fruit was converted into HSV colour space.
- The S component was thresholded, and this component was selected because it is less sensitive to the changes in lighting.
- A closing morphological operator with disk sorting element was then used to fill small holes or gap in the HSV image.
- The threshold image region of interest area and the region of interest border were obtained and roundness of the fruit calculated.
- Then, the threshold image was processed.

Various important methods were used in the process of analysing the fruit pictures to increase the accuracy of classification. Visual inspection work is rather significant in using colour descriptors and the measurements of texture are essential when the surface is not smooth and achromatic. The two mixed are usually advantageous to the performance but the calculation should be retained to the bare minimum. The images of fruits were converted into HSV and GLCM representations like Mean,

Standard deviation, Skewness, Homogeneity, Entropy, Contrast, Correlation, Energy, RMS, Variance, Smoothness, Kurtosis, and IDM were derived, and this is 14 statistical features per image. The grayscale image presented in Figure 5 Plates 1-5 has used area and perimeter measures as the basis of computing the roundness ratio of the grayscale image.

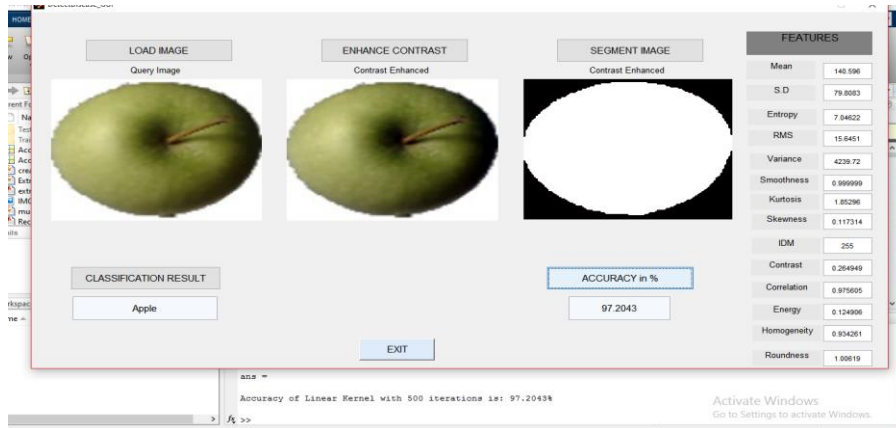


Figure 5. Plate 1: Apple fruit type classification result and accuracy

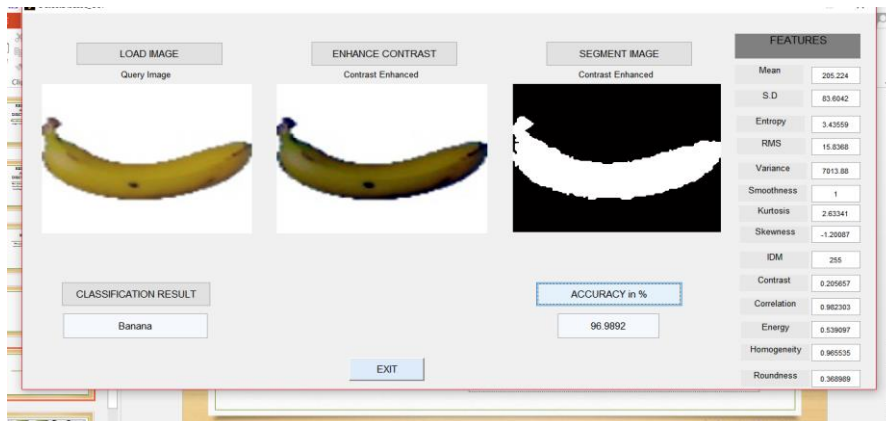


Figure 5. Plate 2: Banana fruit type classification result and accuracy

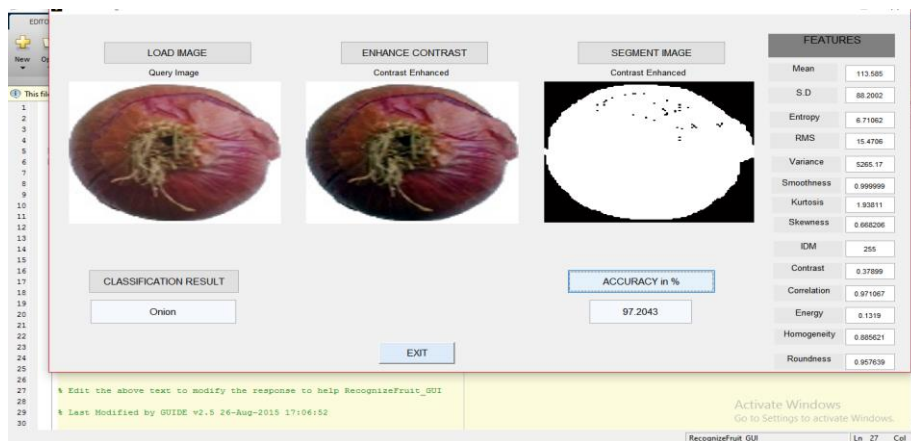


Figure 5. Plate 3: Onion fruit type classification result and accuracy



Figure 5. Plate 4: Pepper fruit type classification result and accuracy



Figure 5. Plate 5: Tomato fruit type classification result and accuracy

Hence, the colour and texture information are complementary and when used together they yield good results of classification.

Table 4 listed results were obtained using test samples taken out from the actual number of 1,120 images, 935 images were used for training and 185 images used for testing. The above algorithm was coded and tested using MATLAB software. Though there are so many methods that are there in this field, this project exposes a different methodology where in the given RGB when converted to HSV combined with Support Vector Machine (SVM) gives 97% accuracy. Apart from the existing methods of extracting colour features, this methodology also uses texture features and statistical feature for all the coefficients.

Table 3. Result from Fruit Recognition System

S. No.	Fruits	Recognition Rate (Using Colour and Texture Features)
1.	Apple (Granny Smith and Braeburn)	97.20%
2.	Banana	96.98%
3.	Onion	97.20%
4.	Pepper (Red and Green)	98.06%
5.	Tomato	97.20%

4. Discussion

The proposed solution was able to build a system with the use of image processing which could accurately recognize and categorize all of the five fruit species, namely those of Apple Braeburn, Apple Granny, Banana, Pepper Green and Pepper Red, as present in the training databank that contained a total of 1,113 photographs (Plate 1). This was divided into 70 percent training (about 780 pictures) and 30 percent testing (about 333 pictures) and Table 3 indicates this in more detail. The images were capturing at different times and days and were saved in RGB at 8 bits per channel which increased sample diversity (Figure 4).

The graphics user interface made on the MATLAB combined with a webcam and the SVM classifier works when it is not connected, giving a successful recognition rate of 97 percentages on the testing images. With RGB images, Region of Interest Extraction Algorithm converted them to HSV, thresholded the S channel to make the images lighting-proof, filled the holes using a morphological closing operator, and found the area, perimeter, and roundness. The following features were obtained on GLCM, Mean, Standard Deviation, Skewness, Homogeneity, Entropy, Contrast, correlation, energy, RMS, Variance, Smoothness, Kurtosis, and IDM (14 in total), followed by area and perimeter of roundness (Figure 5, Plates 1-5).

The obtained 97 percent accuracy in categorizing fruits is better than the previous SVM-based systems (e.g. 90 percent in Zawbaa et al., 2014) and it is comparable to recent MATLAB-based defect detection systems (Bhadouria, 2023). It may be possible to implement lightweight CNNs in real-time on-farm sorting in the future, similar to the case in olive grading (Saedi et al., 2024), but overcome transportation issues through the introduction of AI. This would also decrease the labour dependence in the Nigerian agriculture

The combination of colour and texture improves the classification even though they do not require much in the way of processor performance. This HSV-SVM system was tested on 1,120 images (935 training, 185 testing, Table 4), and produced a new 97 percent accurate methodology to the general colour based methods in literature. The 97% recognition rate of our system (Table 4) beats the 90% and 89% rates of Seng and Mirisae (2009) and Zhang et al. (2016) because of the 1,113-image used and the HSV-GLCM characteristics that deal with variability in the real world. It is slightly lower than that of Aibinu et al (2011), at 99.1, probably because they used controlled conditions when we were working in the field. According to Patel and Patil (2023), the difference in accuracy to dataset diversity ranges between 5-10% which is consistent with ours. Among the limitations, there is sensitivity to the extreme lighting, which can be overcome with CNN improvements (Li et al., 2021) which confirms the feasibility of our approach.

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