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Recognition of Mangoes and Oranges Colour and Texture Features and Locality Preserving Projection

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Abstract: In this paper, a recognition system for classifying and predicting mangoes and oranges has been developed. With the use of support vector machine (SVM) and decision tree algorithm (DTA), classification was done on the images of the fruits gathered locally and publicly into defective, ripe, unripe for local and ripe and unripe for public datasets. The proposed system involves several stages including pre-processing, feature extraction and classification. Images were resized, background distortion was eliminated, colour and texture components were also extracted from the images. Each pre-processed images Histogram and Haralick texture features were extracted as a feature vector and used as transformation inputs. Also, the locality preserving projection (LoPP) was computed on the extracted local features and used as feature for classification. A One-against-One multi-class SVM and fine tree DTA classifier with 30% held out was used for classification. The proposed approach was tested on 328 mangoes and oranges sample images obtained locally and 149 images of public data. Based on the experiment carried out various success rates were recorded on different levels but an excellent classification accuracy of 100% and 92.9% was obtained on the public dataset, 91.3% and 90.2% and 91.1% on the local dataset, 91.3% and 92.2% on the local dataset using LoPP for mango and orange predictions. Mangoes and oranges were categorised, results obtained was 88.6%, 80.4% and 85.6% for public, local and LoPP on local datasets.

Keywords: Colour histogram, Haralick texture features, Multi-class SVM, Fruit recognition, Locality Preserving Projection

1. Introduction

In the automation of fruit quality inspection, grading, and surface defect detection, computer vision and image processing are important [1]. Qualities such as texture, size, colour and surface defect are used in the grading of fruits [2], sorting based on these qualities are done manually in Nigerian markets. The use of an automated process and visual inspection system in fruit industries will increase the sorting quality with less time spent in the process.

Mangoes and oranges are grown extensively and commercially in Nigeria as they are also consumed almost all over the world. The high consumption rate has placed more focus on the sorting procedures especially in terms of reducing losses when they are being transported to other places [3]. These problems can be solved by using a computer vision-based framework. Due to its advantages of high accuracy, high processing speed, reliability, reduction of cost and non-contact detection, computer vision has become an unavoidable technology trend in the production of automated sorting and grading process for fruits [4].

Oranges are commonly grown all over the world, they are used in different food processing and pharmaceutical industries [5], mangoes are also popular due to its taste and nutritional value [6]. Both fruits are needed to be handled carefully as they are perishable, they are mostly sorted manually based on their quality, ripeness stage and other characteristics. After sorting the fruits, they are mostly transported in bulks to markets for consumers and other industries for onward processing to yield other products. Hence the need to have an automated process to classify these fruits efficiently for onward distribution and also to prevent wastage.

The increase in demand for different qualities of fruits at affordable prices makes automated grading and sorting of fruits very important. Image analysis are cost-effective techniques to automatically sort and grade food products [1] thus making it possible to sort fruits like mangoes and oranges produced in the farms according to their quality and maturity level before transporting them to various standard markets using these techniques.

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According to Nandi, Tudu,& Koley in [7] the sorting process is crucial in determining which market fruits will be sent to; factors such as transportation delays and manual sorting by visual check are effortful, time-consuming, and plagued by inconsistency and inaccuracy in judgment. The authors presented an automated technique for scoring and categorizing mangoes based on their maturity levels. Unsorted images of 600 mangoes were sorted using the Gaussian Mixture Model (GMM) to estimate parameters of the individual classes and predict the maturity levels. Their approach was found to be inexpensive and comparable in terms of efficiency.

Since fruits are perishable and do not all ripen at once, their shelf life influences transportation and storage decisions [8]. Authors proposed an automated method for estimating mangoes' shelf life and calculating number of days required for them to mature. The number of surface injuries and maturity time were considered using image arithmetic and thresholding techniques.

Pattern recognition-based model was proposed by Jhawar in [9] to automatically sort oranges, they were classified into four categories based on their maturity levels as; not ripe, semi-ripe, ripe and overripe. The size of the fruits was also predicted into small, medium or large using linear regression technique, edited multi-seed nearest neighbour and nearest prototype. Orange fruit of 160 samples was used for the experiment and success rates of 92.3%, 89.90% and 97.98% were recorded for the closest prototype, edited-multi seed nearest neighbour and linear regression respectively. The author recommended linear regression for predicting the life span of fruit and also detection of damaged orange fruit as it had the best result when compared with the other techniques.

Authors in [10] stated that the process of estimating the shape and size of fruits is labour intensive and time-consuming. A strawberry grading system based on computer vision was developed as part of the research. The algorithm used was based on geometry properties of a kite as the strawberry fruit resembles the shape, the system estimated the diameter, length and angle of strawberry fruits with and without calyx occlusion. They found it challenging to get a reliable and fast processing time but obtained result of 94% and 93% for diameter and length of strawberries without calyx occlusion and 94% and 98% for those with calyx occlusion.

In another study [11], authors proposed an image processing technique which categorized mangoes into six stages based on their skin colour. The experiment considered samples of images of 100 mangoes harvested at early stages and observed at different maturity stages. A total of 24 mango features relating to HSV and RGB were extracted from the images and the most informative feature sets used in the classification of ripening stage were selected using an information gain-based correlation evaluator. Categorization was done using decision tree obtaining a classification accuracy of 96%. The decision tree has a massive advantage in the classification process and a recommendation was made on the use of more data and similar light intensity to reduce errors.

Many colour vision fruits grading systems have been developed including classification of ripe or unripe orange fruits by Kanimozhi and Malliga [12] using the colour coding technique. In this work, the authors recognised red and orange colour fruits conformation and segmented the images, then a database of images was trained to obtain a performance accuracy of 90%. Vyas, et al. [13] developed an algorithm to classify mangoes into various grades using the lab colour model for colour feature extraction from the images. The captured mangoes used for the experiment were in three stages; unripe, semi-ripe and ripe. The authors concluded the method used was accurate as they obtained a classification accuracy of 94.97%. They recommended that performance can be increased by using the texture of the mango as feature parameter.

Razak, et al. [14] implemented an effective algorithm for detecting and sorting mangoes achieving an accuracy greater than 80%; obtaining a score better than human experts. The fuzzy image analysis method was used for the mango grading system; consisting of digital image processing and fuzzy classification system. The system was aimed to replace the human expert burden and make the classification system look more like human classifiers.

An accuracy of 97% was achieved [15] in sorting mangoes automatically using a multiclass SVM classifier. The mangoes were sorted as very good, good and bad.

Authors in [16] implemented image processing device for sorting of citrus fruits and colour grade defected fruits such as oranges, sweet limes and lemons. For the experiment, single view fruit image was captured; contrast, energy, correlation and homogeneity features were extracted using grey level co-occurrence matrix (GLCM). The aim was to classify and assess all citrus fruits into quality batches based on colour which can be used for quality control.

Mangoes were also automatically classified into ten (10) common varieties in India this automatic classification was done by authors in [17]. They used thee multiclass SVM with k-means clustering for classification and background separation. The GLCM was used to extract 13 features from images of mangoes. The classification system was successful achieving an accuracy result of 90%.

Fiona, et al. [18] developed a smart farming technique on citrus fruits, the aim was to replace manual sorting efficiently especially in terms of reducing the time taken to complete the process. For classification and pattern matching, Artificial Neural Network (ANN) was used the technique reduced effort of humans and gave 90% accuracy.

Authors in [19] used a system based on Principal Component Analysis (PCA) for feature extraction and SVM for ripeness stage classification to distinguish bell pepper ripeness stages. Based on their experiment, 93.89 percent classification was reported combining colored HSV histogram and color moments.

Ninawe and Pandey [20] came up with a new fruits identification approach that merged four features analysis methods; shape, size, colour and texture; these features were seen to help in increasing recognition accuracy. Using the KNN algorithm the recognition result of 95% was obtained.

Zhang and Wu [21] presented a technique for accurate and efficient fruit classification based on a multi-class kernel-SVM for accurate. A digital camera was used to capture fruit images, and then a split-and-merge algorithm was used to distinguish the foreground from the background. Colour histogram, texture and shape features were then extracted from each image to form a feature-set; PCA was used to reduce the dimensions of feature space. Three forms of multi-class SVMs were used in the experiments; Winner-Takes-All, Max-Wins-Voting, and Directed Acyclic Graph. In terms of classification accuracy, the Max-Wins-Voting SVM with Gaussian Radial Basis kernel had the best score of 88.2%, while of the Directed Acyclic Graph SVM was the fastest in terms of computation time.

Hussain, et al. [22] Proposed an automated fruit recognition system based on Deep Convolutional Neural Network (DCNN) which considered external environmental changes, they generated a database of 44406 images of fruits consisting of 15 different categories. The method proposed could identify fruits with various challenges with an excellent accuracy rate of 99%.

There has been a widespread and use of computer vision in sorting fruits and estimating the ripeness stages of fruits [23]. Authors in [5] extracted RGB colour space and grey values from images of oranges to separate them into three conditions; ripe, unripe and scaled or rotten. Their work was based on using decision tree classification model, for the experiment they obtained results of 93.13%, 93.45%, 93.24% respectively for accuracy, precision, and sensitivity.

Kumari, et al. [2] used linear SVM for classification of defective and non-defective Indian mangoes into unripe mangoes, ripe mangoes with a surface defect and defected mangoes. For surface detection, K-means clustering and FCM image segmentation methods were used, and for color feature extraction, RGB and HSV color models were used. From RGB and HSV, a total of 6 color features were extracted; RMean, RMedian, GMean, GMedian, BMean, BMedian, HMean, HMedian, SMean, SMedian, VMean, and VMedian and used in classifying mangoes based on their maturity. Performance analysis result obtained using SVM showed 92% accuracy with the K-means clustering method performing better than the FCM method with an accuracy of 87%. For future work, the authors recommended a focus on combining colour and texture features.

In another study in [24], authors proposed a novel scheme called Locality Preserving Projections (LoPP): a dimension reduction algorithm as feature extraction. The neighborhood structure of feature sets is optimally maintained by LoPP, also known as Laplacian eigenmaps. Results obtained showed that LoPP gave better classification result than its counterparts.

Another research in [25] looked at using Coslets a novel transform technique known to better represent images for classification. Coslets was generated by using 1D wavelets in DCT domain. Results revealed that Coslet gave better classification results when used on standard dataset.

In [26], authors classified orange into ripe, unripe and rotten categories using RGB and gray values based on Border/Interior Pixel Classification (BIC) features. Authors also examined the impact of classification algorithm using Naïve Bayes (NB), Artificial Neural Network (ANN) and Decision Tree. Obtaining 93.13%, 93.45% and 93.24% respectively. Authors observed that Decision Tree gave better classification result than NB and ANN.

From reviewed literature, several works have been carried out on automated classification and recognition of fruits with machine learning approach using various classifiers with different success rates recorded. However, not known work has been done on recognition on oranges and mangoes together especially in Nigeria using a combination of colour and texture features. Hence, this paper presents an efficient multi-class image classification system using image processing with colour and textural features for recognition and classification of mangoes and oranges into three categories; ripe, unripe and defective with the aid of image processing toolbox in MATLAB. The study also examined the classification strength of LoPP when applied on the extracted features. Real-life photographs of mangoes and oranges at various stages were sourced locally and publicly[27], [28] and used in the experiment.

Following this section is section 2 which looks at concepts of the study. The study's methodology is listed in Section 3. Following that, section 4 addresses image dataset that was evaluated and presents experimental findings. Section 5 concludes the study.

2. Core Concepts

Mangoes and oranges are common fruits that are grown and consumed all over the world, hence the need to categorize them by their ripening point. Classification is currently done manually and it involves lots of human labour which is stressful and very prone to error. Colour, texture features and Locality Preserving Projection applied as dimensionality reduction technique with SVM and Decision tree algorithms will help in automating this process.

A. Colour features

Colour has been a common function in image classification [29]. For image description, colour is a common and essential feature. A colour histogram is used Colour histogram is an image descriptor that represents the distribution of image intensities values [30].

B. Texture features

Haralick textures are common features in image analysis. To extract the features, image quantization is computed to reduce the grey levels. Haralick, et al. [31] introduced the GLCM technique for quantifying a spatial relationship of pixels in an image. Using suitable statistical descriptors, 14 features are extracted from each co-occurrence matrix [29]. For the experiment conducted, 14 features and the equations used for computation are shown in table I.

C. Locality Preserving Projection (LoPP)

According to [24], LoPP is dimension reduction algorithm that considers the overall structure while retaining the local structure of the input data. when LoPP was applied on some data, it gave a better classification performance than the likes of PCA.

According to [24]: Let there be N number of input data points $(d_1, d_2, \ldots, d_N)$, which are in $\Re^M$.

The LoPP algorithm was computed thus: Step 1: Construct the adjacency graph G of N nodes, such that node i and j are connected if di and dj are similar to each other in any of the following conditions:

1) k-nearest neighbors: if i is one of j's k-nearest neighbors or vice-versa.
2) $\in -neighbors$: Nodes i and j are connected by an edge if $di - dj2 <\in$, where . is Euclidean norm

Step 2: Construct the weight matrix Wt that is a sparse symmetric NxN matrix with weights Wt_{ij} if there is an edge between nodes $iandj, and0$ is there is no edge. Weight matrix can be constructed as follows:

1) Heat-Kernel: $Wt_{mn} = edm - dn2t$, if m and n are related.
2) $Wt_{mn} = 1, iff$ nodes m and n are connected

LoPP objective function solve the following generalized problem:

$$XLX^T a = \lambda XDX^T a \tag{1}$$

where D denotes the diagonal matrix The transformation matrix W is generated by arranging and ordering the eigenvectors of equation 1 and ordered according to their eigenvalues, $\lambda_1, \lambda_2, \ldots, \lambda_l$. Thus, the feature $vectory_i\ of\ input\ d_i$ is obtained as follows: $d_i \rightarrow y_i = A^T d_i \quad \forall i = 1, 2, \ldots, N$

LoPP model will be applied to the extracted features to see if they affect output accuracy.

D. Support Vector Machine (SVM)

The SVM is an efficient supervised classification and regression algorithm with great results [19]. SVM finds the separating optimal hyperplane to solve the classification problem. This is based on the training cases that are put on the support vectors edges [32].

SVM algorithms maximizes the margin around the hyperplane that separates the positive class from a negative class. Provided a training dataset with n samples $(x_1,\ y_1), (x_2,\ y_2), \ldots. (x_n,\ y_n)$ where x_i is a feature vector in a v-dimensional feature space and with labels $y_i \in -1$, 1 belonging to either of two linearly separable classes $C_1 and C_2$ Geometrically, the SVM modelling algorithm seeks an ideal hyperplane with the greatest margin to divide two groups which necessitates solving optimization problem, as shown in equation 2 [19].

$$Maximize \sum_{p=1}^{m} \alpha - \frac{1}{2} \sum_{p,q=1}^{m} \alpha_p \alpha q y_p y_q . K\left(x_p, x_q\right) \tag{2}$$

$$Subject\ to \textstyle\sum_{i=1}^{n} \alpha_i y_i, 0 \leq \alpha_i \leq C$$

where, α_p is the weight given to the training sample x_p. If $\alpha_p \quad > 0, x_p$ is referred to as a support vector. C is a control parameter that is used to trade-off the training accuracy and the model complexity in other to achieve a superior generalization capability can be achieved k is a kernel function, that is used to determine how close two samples are [19].

Various kernel functions have been suggested and extensively used in the past for classification tasks. These kernels are used independently for both discrete and continuous data. However, in this paper the following parameters were used: Quadratic SVM, Kernel function: Quadratic, Kernel scale: Automatic, Box constraint level: 1, Multiclass method: one-vs-one, standardized data: true

E. E. Decision Tree Algorithm (DTA)

As reported in [33], Decision tree algorithms (DTAs) are well-known machine learning techniques that can be used to solve a number of problems, including classification problems. For partitioning datasets, DTA provides a nonparametric process.

DTA, also known as classification and regression tree (CART), uses binary recursive partitions to separate data into homogeneous subsets. To partition the data set into branch nodes, the most discriminative variable is chosen as the root node first. This action is repeated until the nodes are homogeneous enough to be called leaves since they are terminal. As a consequence, leaves represent class labels and branches represent feature combinations that lead to certain class labels in a tree structure.

DTA was chosen for this study because of its popularity, accessibility, and ability to transform large complex datasets

TABLE I. Haralick textural features with equation

Feature	Formula
Angular second moment	$f_1 = \sum_x \sum_y \{p(x.y)\}^2$
Contrast	$f_2 = \sum_{n=0}^{N_{\theta-1}} n^2 i = 1x - y = nNgj = 1Ngp(i,i)$
Correlation	$f_3 = \frac{\sum_p \sum_q (p\ q) - \mu_x\ \mu_y}{\sigma_x\ \ \sigma_y}$
Variance	$f_4 = \sum_x \sum_y (i - \ \mu)^2\ p(x,\ y)$
Inverse Difference Moment	$f_5 = \sum_x \sum_y \frac{1}{1+(x-y)^2}\ \ p(x,\ y)$
Sum average	$f_6 = \sum_{n\ =2}^{2N_g} ip_{x+y}(n)$
Sum variance	$f_7 = \sum_{i=2}^{2N_g} (i - \ f_8)^2\ \ p_{x+y\ (i)}$
Sum entropy	$f_8 = - \sum_{n\ =\ 2}^{2\ N_g} p_{i+j}(n) log \left\{ p_{i+j}(n) \right\}$
Entropy	$f_9 = \sum_i \sum_j p(x,\ y)\ \log(p(x.\ y))$
Difference variance	$f_{10} = \ variance\ of\ \ p_{x-y}$
Difference entropy	$f_{11} = -\sum_{i=0}^{N_{g-1}} p_{m-n(i)} \log\{p_{m-n}(i)\}$
Information measure of correlation I	$f_{12} = \frac{HXY - HXY1}{max\{HX,\ HY\}}$
Information Measure of correlation II	$f_{13} = (1 - exp[-2.0(HXY2 - HXY)])\frac{1}{2}$ $HXY = -\sum_x \sum_y P(x,y)\ \ log(p(x,y))$ $where HX and HY are entropies of p_x and p_y$ $HXY1 = - \ \sum_x \sum_y P(x,y) \log\{P_m(x)\ \ p_n\ \ (y)\}$ $HXY2 = -\sum_m \sum_n P_X(m) P_y(n)\ log \left\{ P_x(m)\ P_y(n) \right\}$
Maximal correlation coefficient	$f_{14} = (second\ largest\ eigenvalue\ of\ Q\ )^{\frac{1}{2}}$ $where\ Q(m,n) \sum_k \frac{P(m,k)P(n,k)}{P_x(m)P_y(n)}$

into simple yet information-rich graphical displays.

3. Methodology

Pre-processing, feature extraction, feature dimension reduction, and classification are the four phases of the proposed solution. The structure of the proposed method for identifying mangoes and oranges is shown in Figure 1.

- Pre-processing: To reduce the color index, the proposed technique resized all images from 4160x3120 to 134 x 100 pixels during the pre-processing step. The graphcut background subtraction technique was used to remove the background of each image. Background subtraction is a technique for distinguishing moving parts from static cameras by segmenting them into foreground and background [34].
- Feature Extraction: For feature extraction phase, colour histogram and haralick texture features were extracted as features from the images.
- Dimension reduction: For dimension reduction, LoPP will be used on the colour and combination of colour and texture features. This is done to improve on the classification performance.
- Classification: For the classification phase, the SVM and DTA algorithms were used, the fruits were classified into ripe, unripe and defective mangoes and oranges. Figures 2 (a) and (b) show sample images of unripe, ripe and defective mangoes and oranges before and after segmentation.

A. Dataset

The experiments' dataset was sourced locally and was based on a standard dataset accessible on the internet.

1) Local Dataset

We developed a dataset with 328 real-life photographs of mangoes and oranges in various categories. Color JPEG images with a resolution of 4160x3120 pixels were taken with a Samsung phone camera with a resolution of 13 megapixels. True sample images of mangoes were used in the experiments. They were obtained from farms in Nigeria's Kaduna Metropolis, and they were at various stages of classification. Based on what was collected as unripe, ripe, and defective mangoes and oranges, the dataset was divided into three groups. A total of 328 mango and orange photos were captured, consisting of 156 mangoes and 172 oranges, with 75, 41, and 40 unripe, mature, and defective mangoes, respectively. Unripe oranges accounted for 44, while ripe and defective oranges accounted for 60 and 68, respectively. Both preparation and research were performed for these samples.

2) Standard Dataset

Mango dataset was also obtained publicly at [27]. These samples of mangos are in different maturity stages. A digital camera makes up the image acquisition system (EOS 550D, Canon Inc., Japan). The camera was used to capture images with a resolution of 0.03mm/pixel and a resolution of 5185

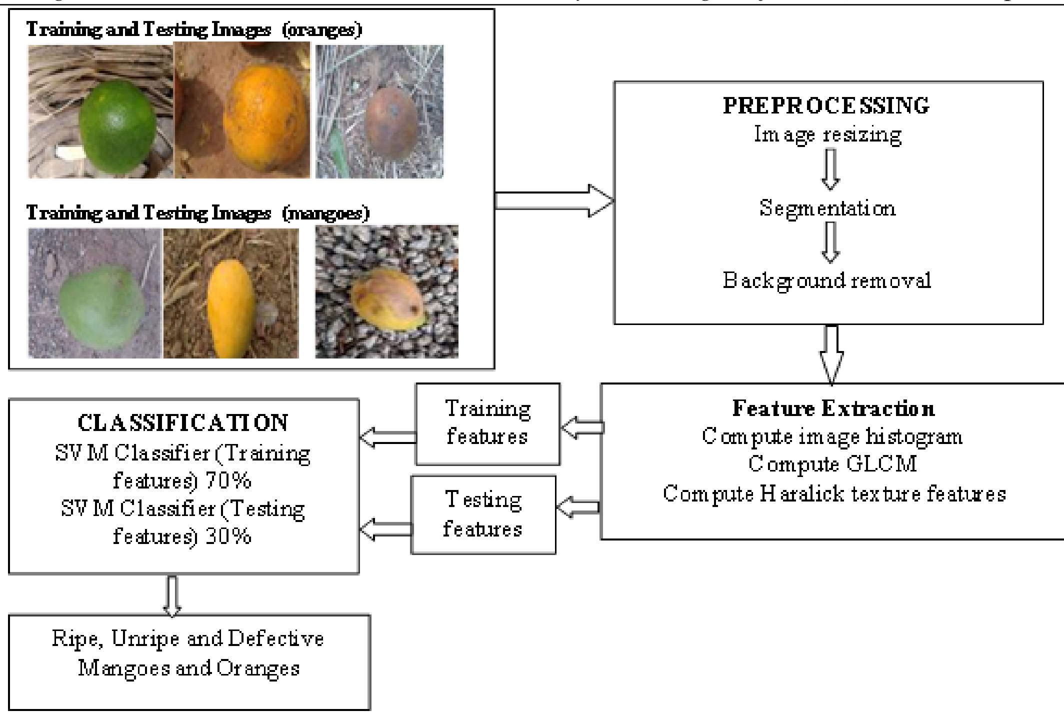


Figure 1. The Architecture of the Proposed System

x 3456 pixels. To save space, images are downloaded at a resolution of 1200 x 800 pixels. Table II displays the parameter settings for the camera that was used for the capture.

The full detailed setup of the system for capture can be found online at [27].

Based on the available samples, the dataset will be grouped into two (2) classes; 49 ripe and 52 unripe categories. This is because the dataset does not contain rotten mangos.

Similarly, the orange dataset was obtained publicly at [28]. A total of 759 photos of safe and unhealthy oranges and leaves are included in the dataset.

Every picture has a resolution of 72 dpi and measures 256 * 25 pixels. Under the supervision of Dr. Basharat Ali Saleem, photos were collected in the Sargodha region of Pakistan and manually annotated as Black spot, Canker, Greening, Scab, and safe, yielding a total of 150 orange images.

For our experiment, the images will be regrouped into two (2) categories of 24 ripe and 24 unripe respectively. This is because the dataset does not contain rotten oranges.

4. Experimental Results

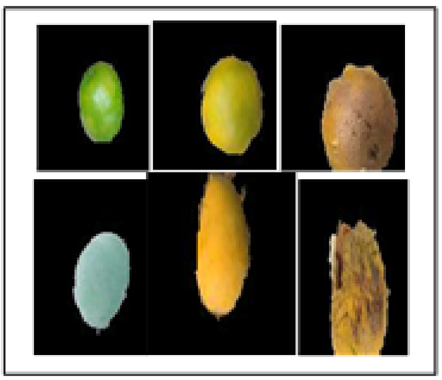
The experiments were carried out using a dataset gathered locally and publicly. The local dataset contained images of mangoes and oranges at various stages of their ripeness, the dataset was divided into 3 classes representing unripe, ripe and defective mangoes and oranges. While the public dataset was grouped into two categories of ripe and unripe respectively.

TABLE II. Haralick textural features with equation

X Resolution	72 inches
Y Resolution	72 inches
Exposure time[s]	$frac14$
F-Number	22.0
ISO speed ratings	800
Shutter speed [s]	$frac14$
Aperture	F22.6
Flash	No flash
Focal length [mm]	35
Colour space	sRGB
Compression setting	Fine
White balance	Cloudy

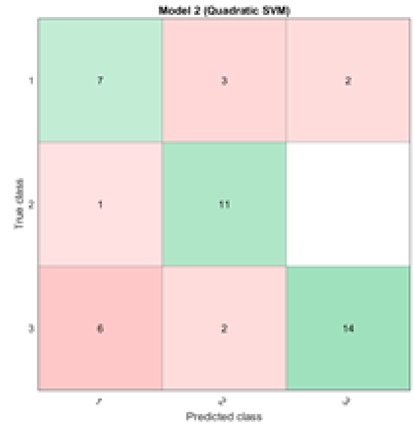
The proposed approach was tested in MATLAB using SVM and DTA algoriths for both training and testing with 30% held for testing. The features used for classification were coloured histogram and haralick texture features and LoPP on the extracted features. The results are shown in Figs 3 - 9 and reported in subsequent sections. Results were reported as colour histogram, texture, their combination and LoPP on each extracted features for mango prediction. Similarly, colour histogram, texture, their combination and LoPP on the extracted features for orange prediction. Fi-

(a)

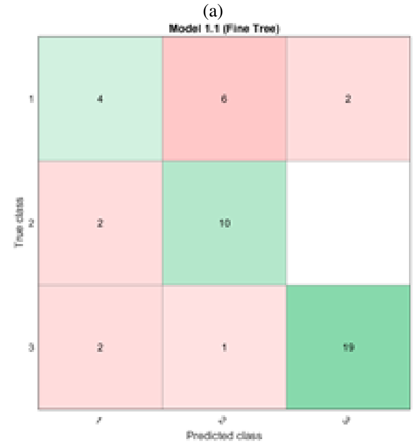


(b)

Figure 2. Mangoes and Oranges samples before (a) and after (b) Segmentation



(a)



(b)

Figure 3. Confusion Matrix showing the prediction of mangoes using SVM 3a and DTA 3b on colour histogram

nally, a combination of the colour histogram and texture and LoPP on the combined features for mango and orange predictions. The LoPP was tested on only the dataset gathered locally.

A. Mango Prediction using Colour Histogram Features for Local Dataset

After the experiment, an accuracy of 69.6% and 71.7% was obtained using quadratic SVM and fine tree DTA. Figure 3 shows the confusion matrix of the results obtained.

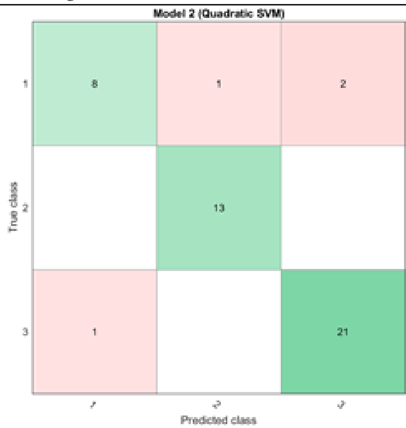
The confusion matrix in Fig. 3 shows the number of observations obtained from predicting mangoes using colour Histogram features, the ripeness stages are grouped into three classes; classes 1, 2 and 3 for defective, ripe and unripe mangoes respectively, the numbers of correctly observed predicted mangoes as defective, ripe and unripe were 7, 11 and 14 (Fig. 3a) respectively for classes 1, 2 and 3 using SVM and 4, 10 and 19 using DTA (Fig. 3b). Five (5) defectives mangoes were predicted as 3 ripe and 2 unripe respectively. One ripe mango was predicted as defective while 8 unripe were predicted as 6 defective and 2 ripe mangoes respectively using SVM classifier (Fig. 3a). Using the DTA classifier, out of 12 defective mangoes, 8 were wrongly predicted as 6 ripe and 2 unripe. From the 12 ripe mangoes, 2 were predicted as defective. Twenty two mangoes were unripe, out of which 3 were wrongly predicted as 2 defective and 1 ripe (Fig. 3b).

The ROC Area Under Curve (AUC) was 0.78 and 0.65 for SVM and DTA classifiers. This showed the classification performance at 78% and 65% which indicates very good classification performance.

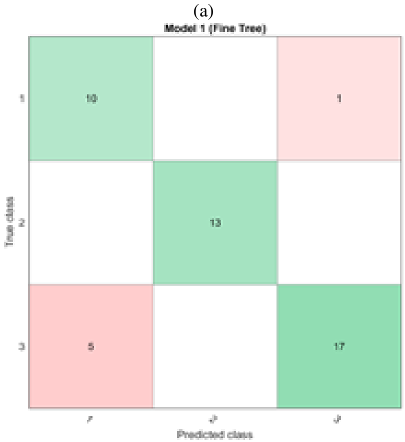
B. Mango Prediction using Haralick Texture Features for Local Dataset

After the experiment, the haralick texture features had an accuracy recognition rate of 91.3% and 87.0%. Fig. 4 shows the confusion matrix of the results obtained.

The confusion matrix in Fig. 4 shows the number of observation obtained in predicting mangoes using haralick texture features. From the matrix, classes 1, 2 and 3 represent defective, ripe and unripe mangoes respectively. Using SVM classifier, eight defective mangoes were predicted correctly while 3 were predicted as 1 ripe and 2 unripe mangoes. All 13 ripe mangoes were correctly predicted.

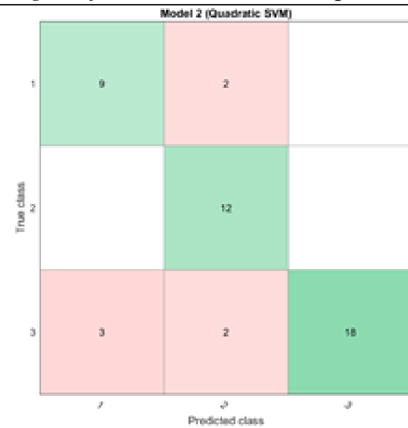


(a)

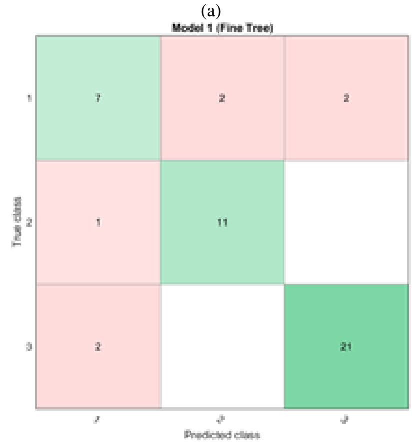


(b)

Figure 4. Confusion Matrix showing the prediction of mangoes using SVM 4a and DTA 4b on haralick texture



(a)



(b)

Figure 5. Confusion Matrix showing the prediction of mangoes using SVM 5a and DTA 5b on histogram and haralick texture features

One out of the 22 unripe mangoes was predicted as defective (Fig 4a). In the case of DTA classifier, 10, 13, and 17 were predicted correctly, leaving 1 defective predicted as unripe and 5 unripe predicted as defective (Fig 4b).

ROC AUC values stood at 0.89 and 0.89 giving 89% each for SVM and DTA classification performance respectviely.

C. *Mango Prediction using Colour Histogram and Haralick Texture Features for Local Dataset*

After the experiment, an overall accuracy of 84.8% each was obtained using SVM and DTA classifiers. Fig. 5 shows the result obtained using confusion matrix.

The confusion matrix in Fig. 5 shows the number of observation obtained in predicting mangoes using the colour histogram and haralick textures as features. From the matrix, classes 1, 2 and 3 represent defective, ripe and unripe mangoes respectively. Correctly predicted values are 9, 12, 18 and 7, 11, 21 using SVM and DTA classifiers to predict mangoes. Seven mangoes were wrongly predicted, 2 out of 11 defectives were ripe, 5 out of 23 unripe were 2 ripes and 3 defectives (Fig 5a). Similarly, 7 mangoes were wrongly predicted as 2 ripe, 2 unripe, 1 ripe and 2 defective for defective, ripe and unripe mangoes respectively.

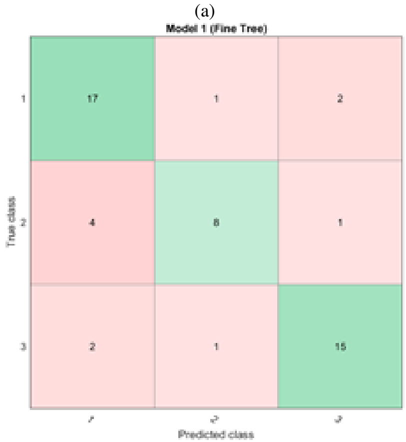
SVM and DTA AUC curves were 0.94 and 0.82 which indicated excellent classification performance.

D. *Orange Prediction using Colour Histogram Features for Local Dataset*

After the experiment, an accuracy of 80.4% and 78.4% was obtained using SVM and DTA algorithms. Fig. 6 shows the confusion matrix of the results obtained.

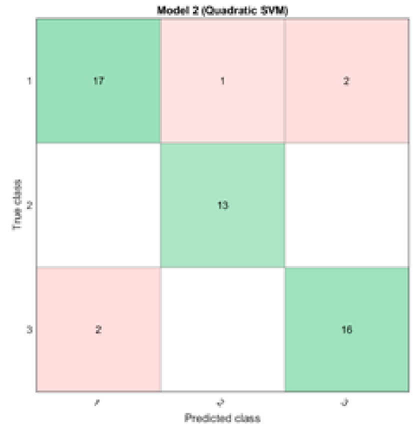
The confusion matrix in Fig. 6 shows the number of observations obtained from predicting oranges, the ripeness stages are grouped into three classes; classes 1, 2 and 3 for defective, ripe and unripe oranges respectively. The numbers of correctly predicted oranges as defective, ripe and unripe were 13, 11 and 17 (Fig 6a) respectively for classes 1, 2 and 3 using SVM and 17, 8 and 15 using DTA (Fig 6b). Seven defectives oranges were predicted as 4 ripe and 3 unripe respectively. One each ripe orange was predicted as defective and unripe while 1 unripe was

(a)

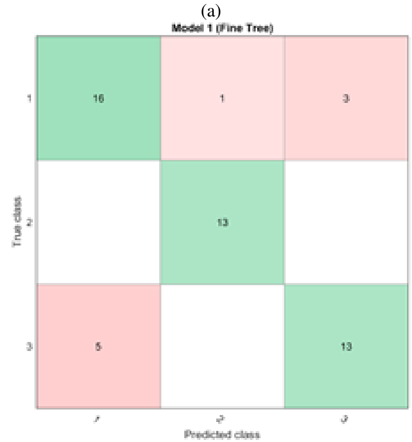


(b)

Figure 6. Confusion Matrix showing the prediction of oranges using SVM 6a and DTA 6b on histogram



(a)



(b)

Figure 7. Confusion Matrix showing the prediction of oranges using SVM 7a and DTA 7b on haralick texture

predicted as 1 defective orange using SVM classifier (Fig 6a). Using the DTA classifier, out of 20 defective oranges, 3 were wrongly predicted as 1 ripe and 2 unripe. From the 13 ripe oranges, 4 were predicted as defective while 1 was unripe. Twenty two oranges were unripe, out of which 3 were wrongly predicted as 2 defective and 1 ripe (Fig 6b).

The AUC was 0.89 and 0.87 for SVM and DTA classifiers. This showed the classification performance of 89% and 87% which indicates excellent classification performance.

E. Orange Prediction using Haralick Texture Features for Local Dataset

After the experiment, the haralick texture features had an accuracy recognition rate of 90.2% and 82.4%. Fig. 7 shows the confusion matrix of the results obtained.

After the experiment, the haralick texture features had an accuracy recognition rate of 90.2% and 82.4%. Fig. 7 shows the confusion matrix of the results obtained.

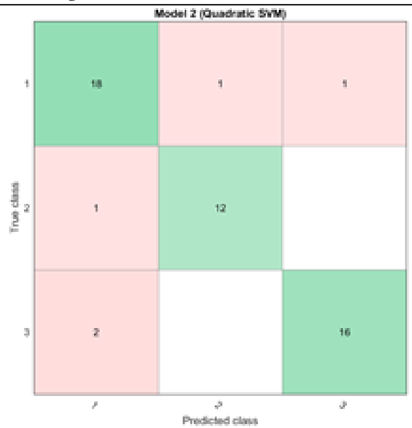
The confusion matrix in Fig. 7 shows the number of observation obtained in predicting oranges using haralick texture features. From the matrix, classes 1, 2 and 3 represent defective, ripe and unripe mangoes respectively. Using SVM classifier, seventeen defective mangoes were predicted correctly while 3 were predicted as 1 ripe and 2 unripe. All 13 ripe mangoes were correctly predicted. Two out of the eighteen unripe oranges were predicted as defective (Fig 7a). In the case of DTA classifier, 16, 13, and 13 were predicted correctly, leaving 4 defective predicted as 1 ripe, 3 unripe and 5 unripe predicted as defective (Fig 7b).

ROC AUC values stood at 0.92 and 0.83 giving 89% each for SVM and DTA classification performance respectively.

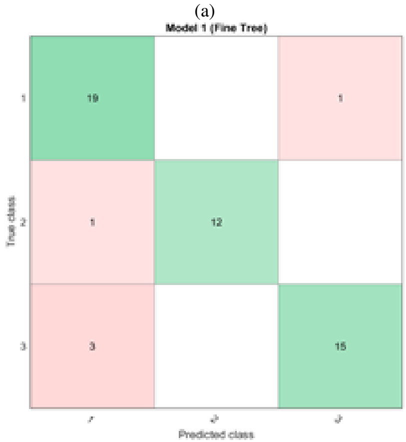
F. Orange Prediction using Colour Histogram and Haralick Texture Features for Local Dataset

After the experiment, an overall accuracy of 90.2% each was obtained using SVM and DTA classifiers. Fig. 8 shows the result obtained using confusion matrix.

The confusion matrix in Fig. 8 shows the number of observation obtained in predicting oranges using the

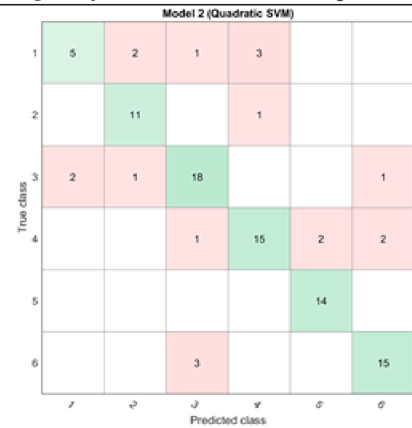


(a)

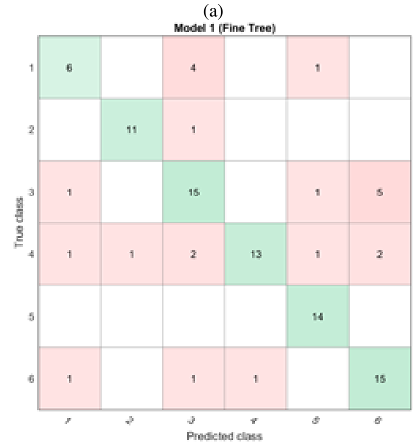


(b)

Figure 8. Confusion Matrix showing the prediction of oranges using SVM 8a and DTA 8b on colour histogram and haralick texture features



(a)



(b)

Figure 9. Confusion Matrix showing the prediction of mangoes and oranges using SVM 9a and DTA 9b on colour histogram and haralick texture features

colour histogram and haralick textures as features. From the matrix, classes 1, 2 and 3 represent defective, ripe and unripe oranges respectively. Correctly predicted values are 16, 12, 16 and 19, 12, 15 using SVM and DTA classifiers for prediction. Five oranges were wrongly predicted, 1 each out of the 20 defectives were ripe and unripe, 1 out of 13 ripe was defective and 2 out of 18 unripe were defective (Fig 8a). Similarly, 5 oranges were wrongly predicted as 1 unripe, 1 defective and 3 defective for defective, ripe and unripe oranges respectively.

SVM and DTA AUC curves were 0.94 and 0.91 which indicated excellent classification performance.

G. Mango and Orange Prediction using Colour Histogram and Haralick Texture Features for Local Dataset

After the experiment, an accuracy of 80.4% and 76.3% was obtained using SVM and DTA classifiers. Fig. 9 shows the confusion matrix obtained for predicting mangoes and oranges using the colour histogram and haralick texture features.

Fig. 9 shows the confusion matrix of the number of observations using the colour histogram and harlalick texture features to predict classes of mangoes and oranges as defective, ripe and unripe respectively. There are 6 classes indicated; classes1, 2 and 3 defective, ripe and unripe mangoes while 4, 5 and 6 represent defective, ripe and unripe oranges. For the defective class 1, 5 were correctly predicted as defective while 6 were wrongly predicted, 11 were correctly predicted as ripe in class 2 with 1 wrongly predicted. Eighteen unripe mangoes were correctly predicted with 4 wrongly predicted in class 3. For oranges, 15 defective were correctly predicted while 5 were wrongly predicted in class 4. Fourteen oranges were correctly predicted as ripe and 15 were also correctly predicted as unripe orange for classes 5 and 6. For the wrongly predicted unripe oranges in class 6, the value stood at 3 (Fig 9a).

In (Fig 9b), For the defective class 1, 6 were correctly predicted as defective while 5 were wrongly predicted, 11 were correctly predicted as ripe in class 2 with 1 wrongly predicted. Fifteen unripe mangoes were correctly predicted with 7 wrongly predicted in class 3. For oranges, 13 defective were correctly predicted while 7 were wrongly predicted in class 4. Fourteen oranges were correctly predicted as ripe in class 5 while 15 correctly predicted in class 6 wiith wrongly predicted as 3.

The AUC was 0.92 and 0.89 for SVM and DTA classifiers. This showed the classification performance of 92% and 89% which indicates excellent classification performance.

Table III shows the various accuracies obtained from extracted features on both local and public datasets and when LoPP was computed on the features extracted from local dataset.

From table III, it is clear that texture had more discriminating power over the colour recording higher average accuracies of 94.6% and 87.8% for mango and orange fruits classifitcation. From results obtained, LoPP improved the recognition accuracies when used on the orange fruits with the two classifiers.

5. Conclusions and Future Work

This paper presents a fruits recognition system that predicts ripe, unripe and defective mangoes and oranges based on multi-class SVM and DTA algorithms using the colour histogram and haralick textural features. The experiment carried out showed that extracting features using the haralick textures on the images had the best overall accuracy result with 94.6% and 87.8% obtained on mangoes and oranges. Further experiment was also carried out using the LoPP dimension reduction algorithm on the extracted local features, obtaining 93.5% and 92.2% for mangoes and oranges respectively.

Future work will focus on adding other fruits such as a banana to the systems and compare if there is a relationship in their ripeness stages.

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TABLE III. Accuracies Obtained from Experiments Conducted

Fruit Feature	Public Data		Local Data		Ave	LoPP	
	SVM	DTA	SVM	DTA		SVM	DTA
M_Hist	100	86.7	69.6	71.7	82	69.6	71.7
M_Text	100	100	91.3	87.0	94.6	91.3	93.5
M_H+T	96.7	100	84.8	84.8	91.6	71.7	73.9
O_Hist	57.1	35.7	80.4	78.4	62.9	84.3	82.4
O_Text	92.9	85.7	90.2	82.4	87.8	92.2	90.2
O_H+T	85.7	57.1	90.2	90.2	80.8	90.2	90.2
M+O_H+T	88.6	81.8	80.4	76.3	81.8	85.6	69.1
Average	88.7	78.1	83.8	81.5	83.1	83.6	81.6

The following are the definition for the acronyms:
M_Hist – Mango with histogram features
M_Text – Mango with texture features
M_H+T – Mango with histogram and texture
O_Hist – Orange with histogram features
O_Text – Orange with texture features
O_H+T – Orange with histogram and texture
M+O_H+T – Mango and Orange with histogram and texture features
Ave – Average

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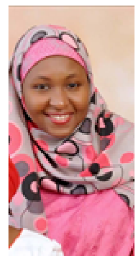

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