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Detection of Soya Beans Ripeness Using Image Processing Techniques and Artificial Neural Network

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Authors' contributions

This work was carried out in collaboration between all authors. Author UFA designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors MAA and SD managed the analyses of the study. All authors read and approved the final manuscript.

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ABSTRACT

The use of technology in agriculture has paved ways for new farming techniques across the globe and the benefits cannot be overemphasised. These benefits include an increase in the quality and quantity of crops produced, minimising cost of farming, providing suggestions for prompt action among others. Traditionally, to detect the ripeness of soya beans, farmers rely on a change in colour of leaves from green to brown, this process cannot be fully reliable as the colour is subjective to human naked eyes, and failure to harvest when ripe causes the seed pods to burst which reduces the crops expected to harvest. The research aim at detecting the ripeness of soya beans. The research employs the use of colour and texture features of leaves through image processing techniques in the pre-processing phase and artificial neural network for the detection of ripeness with the aid of MATLAB as the simulation tool. An accuracy of 95.7% is obtained in the classification of the various categories of soya beans leaves.

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1. INTRODUCTION

Advancement in information and communication technology has proved to be a useful tool in our daily activities, of which agriculture is not an exception to these immense benefits. The application of technology in agriculture has paved ways for new farming methods across the globe and the benefits cannot be overemphasised. These benefits include an increase in the quality and quantity of crops expected to harvest, reduction in the cost of farming, providing suggestions for prompt action among others. As stated by [1] that one of the methods used in improving agricultural activities is *image processing*. [2] note that image processing does not only deal with taking images as its input and producing them as output, but also incorporates the processes that extract image features/attributes used for object recognition. Thus, digital image processing implies the processing of images with the aid of a computer. The use of image processing has a wide range of applications; from image analysis to computer vision. The application of image processing to agriculture involves the extraction of features which uniquely identifies an object to perform the needed task. These features include the shape, size, colour and texture of plants/crops. For instance, according to [3], colour provides helpful information in estimating the maturity and examining the freshness of fruits. This is because the colour is one of the most important attributes that are related to fruit identification and serves as a good indicator of ripeness. Thus, the ripeness of crops can also be detected using colour through the application image processing techniques.

Soya beans are among the major industrial and food crops grown in every continent because of its nutritive and economic values, and Nigeria is not an exception to these immense benefits [4]. The content of a soya bean is mainly protein and its by-product are used to feed animals. Soya bean plant also improves soil fertility. The harvesting period of soya beans is between 3-4 months (including other signs on the features of the plant) [4]. It is recommended that soya beans should be harvested when the leaves and seed pod have turned to brown [5]. This is because delaying the harvest of soya beans (i.e. after the leaves and pods turned from green to brown) will lead to excessive loss of the crop. The harvesting can be done by cutting the ripe soya plant from the ground level using a cutlass, a hoe or a sickle. Therefore, it is desirable to have a technique of immediately detecting the ripeness of soya beans in order to harvest the plant without excessive loss. This can be achieved by identifying the stages of the leaves of the soya bean plant using machine learning techniques such as Artificial Neural Network (ANN). [6] defines the neural network as a discipline that models the biological nervous system in processing data. The model consists of neurons that are interconnected, where each connection is attached to a certain weight that can be adjusted during the training phase. ANN can be supervised learning (requiring training and the output are known) or unsupervised learning (where the output is not known and does not require training).

The succeeding sections give an overview of related works, the methodology adopted for the research, results and evaluation, conclusion and future work, and reference.

2. RELATED WORKS

Various researchers have been carried out to detect the severity of diseases that affect plants, detect/grade the quality of fruits and detect weeds plant with aid of different classifiers as follows.

[7] propose a novel approach to detecting the severity of a disease using three parameters (Infection per Region IPR, Disease Severity Index DSI and Disease Level Parameter DLP) and classify the disease of soya beans using the leaves of the plant. The approach involves image acquisition, pre-processing (Enhancement and Segmentation) and Classification based on neural networks. Textures and colour features are extracted which serves as an input and the output are the different soya beans diseases. An accuracy of more than 90% is achieved in classifying soya beans foliar diseases.

Similarly, [8] propose a method of measuring the severity of soya beans rust using image processing techniques (for conversion, enhancement and segmentation) and apply a neural network to classify the severity of the disease using colour features. The ratio of Infected Area is used to determine the quantification of the percentage of soya beans rust. The method shows that measuring the severity in hue saturation intensity model yielded the accurate result compared to other colour models.

In addition, [9] proposed a method of detecting defects of coffee bean based on its roundness, area and perimeter. Image processing techniques are used for conversion of RGB image to binary image and a threshold value is set based on the metric obtained to distinguish between good or bad coffee bean. Within the sample of 100 coffee bean used, 78.32% are classified as good coffee bean, 19.68% are classified as bad coffee bean and 2% results in a false detection. This approach is tailored to the only coffee bean as other seeds/beans have different forms of defects.

[10] also proposed an approach to determine the different types of olives based on the colours (either green or black) or sizes (either big or small) of the seeds. Image processing techniques are used as a pre-processing step and artificial neural networks (multilayer perceptron) is used as the classifier. The results obtained shows an accuracy of 90% in classifying different types of olives. This approach is also best suited for fruits with single dominant colour but not a fruit with mixed colour.

[11] implement a method of classifying the ripeness of banana into seven stages of ripeness. Colour features and three positions in the banana are considered for the study. The classification is done using support vector machine with radial basis function and linear kernel fiction. An accuracy of 96.5% is obtained when using the radial basis function which shows an increase of 1.5% over linear kernel function.

[12] also propose an approach of grading apples by using support vector machine to classify apples as either green or red. A threshold-based segmentation was used to separate object in focus (apple) from the background and the RGB components were converted to hue saturation value (HSI) components. The proposed approach effectively classifies apples as either green or red with 100% accuracy. This approach is only effective when the object has a single colour (like apple as either red or green).

[13] proposes a novel method for extracting the portion of affected regions of soya beans leaf based on modified salient regions. The method uses low-level features of luminance and colour features together with multi-scale analysis to determine saliency maps in images and applied K-means clustering for segmentation. The results obtained shows that the method has successfully detected the diseases on soya beans leaves in the presence of excessive background.

3. RESEARCH LIMITATION

Based on the reviewed literatures above, not only do diseases or weed plants reduce the expected crops to harvest, but that in some crops, failure to do the right thing (this can even be harvesting when they are ripe) at the right time can even lead to massive loss, and one of such type of crop is soya beans plant. Hence, a means of detecting the ripeness of soya beans so as to reduce the losses cannot be neglected.

4. METHODOLOGY

The approach adopted for detecting the ripeness of soya beans is depicted in Fig. 1.

I. Image Acquisition: The images of soya beans leave of various categories ranging from ripe leaf (but not ready for harvest, usually yellow in colour), unripe (purely green), unhealthy leaf (that is diseased leaf usually in mix colour of green, brown and grey) to fully ripe leaf (purely brown in colour) are captured using a digital camera (Sony with 20.1 megapixel and 5x optical zoom). The images are captured from a farm located 2 kilometres East of Birnin Gwari Local Government Area and within Kaduna city metropolis of Kaduna State at around 11.00am. The images are captured under uncontrolled environment, to obtain their natural colour without introducing any variation in intensity/brightness to the images. Sixty samples of unhealthy and healthy leaves of soya beans are used, sixty sample of ripe not ready for harvest and seventy-five samples of ripe ready for harvest are used during training and testing the designed neural network. Various categories of soya beans are show in Fig. 2.

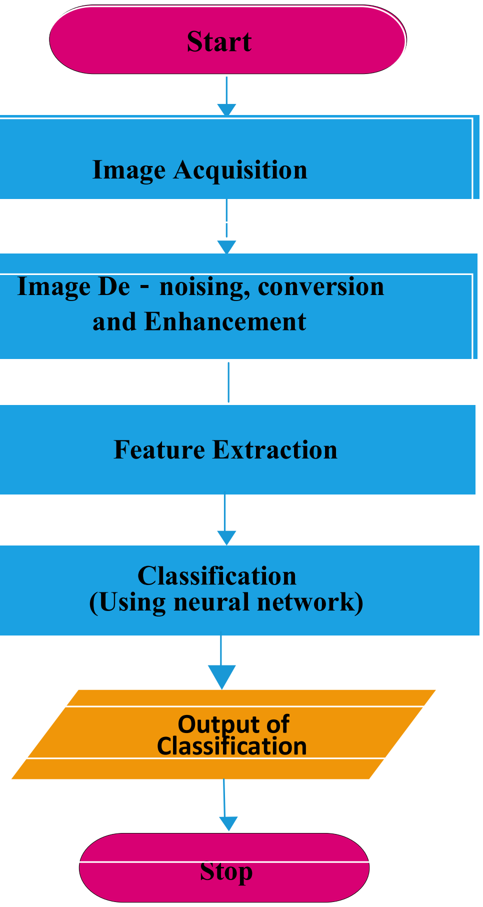

Fig. 1. Flowchart of the proposed system

A: Healthy leaf of soya bean

B: Ripe leaf of soya bean

C: Ripe not ready leaf of soya bean

D: Diseased leaf of soya bean

Fig. 2. Categories of soya beans Leaves

II. Image Conversion, De-noising and Enhancement: The captured images in their red, green, blue (RGB) colour model is converted to hue, saturation, value (HSI) colour model. The hue describes the colour attribute, saturation measures the amount of white colour mixed with pure colour and intensity gives the brightness. According to [2], HSI model is an ideal tool used in image processing and when humans view a colour, they describe it in its colour form, thus, the model becomes an intuitive form of description for humans. To convert the RGB to HSI, we used the below formulas.

$$H = \begin{cases} \theta & if\ B \leq G \\ 360 - \theta & if\ B > G \end{cases} \tag{1.1}$$

Values for hue varies across the axis from 0^0 to 360^0, with

$$\theta = cos^{-1}\left\{\frac{\frac{1}{2}[(R-G)+(R-B)]}{[(R-G)^2+(R-G)(G-B)]^{1/2}}\right\} \tag{1.2}$$

The saturation component is obtained by

$$S = 1 - \frac{3}{(R+G+B)}[\min(R,G,B)] \tag{1.3}$$

The intensity is obtained

$$I = \frac{1}{3}(R+G+B) \tag{1.4}$$

The R, G, and B variables in equations (1.1) to (1.4) represents the red, green, and blue component of an RGB image and are normalised in the range of [0,1]. After converting the images, the images are de-noised. Noise is variation in the intensity of an image and the principal source of this noise is either from acquisition or transmission [2]. Therefore, to denoise the images, the intensity component of HSI image is extracted and a filter is applied. A filter is a sub-image used to modify the original image [2]. In this research, a 3x3 averaging filter is used so as not too blurred desirable features of an image.

III. Feature Extraction: Features are the attribute or properties that represent an object. These features vary by the type of object being focussed. According to [14], feature extraction involves the manipulation and transformation of input data into a set of features that uniquely identifies or represents an object (image). The features of an image are its shape, colour and texture. The use of colour and texture is to ensure unique identification of each leave category. The algorithm used for colour extraction is as follows:

Algorithm: Colour extraction
Input: RGB image
Output: Colour features (HSI Components)
Begin

1. *Read the RGB image*
2. *Convert the RGB image to HSV image*
3. *Extract the hue, saturation and intensity component from RGB image.*
4. *For each of the components, compute the mean and standard deviation*
5. *Save the result of step 4.*

End.

To extract the texture features, Gray level Co-occurrence Matrix is used and the statistical parameters such as energy, contrast, correlation and homogeneity were extracted [15,16,17,18]. The algorithm used is as follows;

Algorithm: Texture features extraction
Input: RGB image
Output: Texture Features
Start

1.0 Read the enhanced image and convert it to grey
2.0 Calculate the GLCM from four directions using the image obtained in step 1.0
3.0 Extract the statistical parameters using the value of GLCM obtained in step 2.0
4.0 Save the values of those parameters

Stop

IV. Image Classification: According to [19], an image classification, pixels are categorised based on certain criteria, that is, if a pixel certifies the criteria, it is selected, because the pixel represents the pattern we recognise. This can be achieved with the aid of data trained by the classifier. However, in this research, ANN is used in the classification process, that is to classify the input features into been ripe, unhealthy leaf, unripe or ripe but not ready for harvest, because ANN is noise tolerant, can predict the category of inputs it hasn't train and one of the most widely used classifier in classifying agricultural produce.

5. EVALUATION AND RESULTS

The designed neural network of the proposed scheme can be evaluated using the various plots obtained during the training phase of the network. The plots include confusion matrix plot, performance plot and receiver operating characteristics plot.

a) Confusion Matrix: Is a table that describes the actual performance of a classification model. It consists of values and percentage for true classification of a particular dataset. Fig. 3 is the confusion matrix obtained after the training.
b) Performance Plot: It shows the performance function versus the iteration number (epoch) by plotting test, validation and training performance. The vertical axis is the cross-entropy in the range 10^{-2} to 10^{0} [15] and the horizontal axis in the range of 0 to 40 represents the number of iterations (epoch). The blue, green and red curves are the curves for training, validation and test respectively as shown below.
c) Receiver Operating Characteristics: This is also a metric for assessing the quality of classifier. It plots the true positive rate (sensitivity) TPR versus the false positive rate FPR (specificity) as the threshold is varied. The below figure is the ROC of the designed neural network of the research.

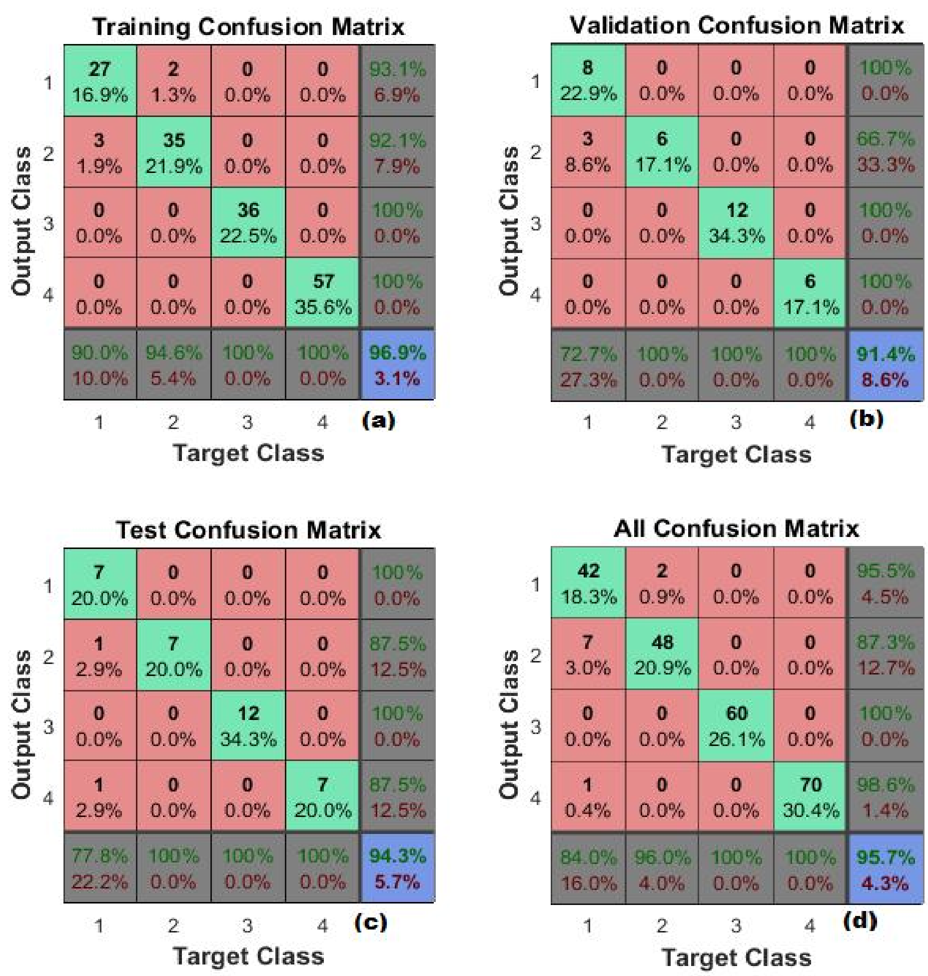

Fig. 3. Confusion matrix

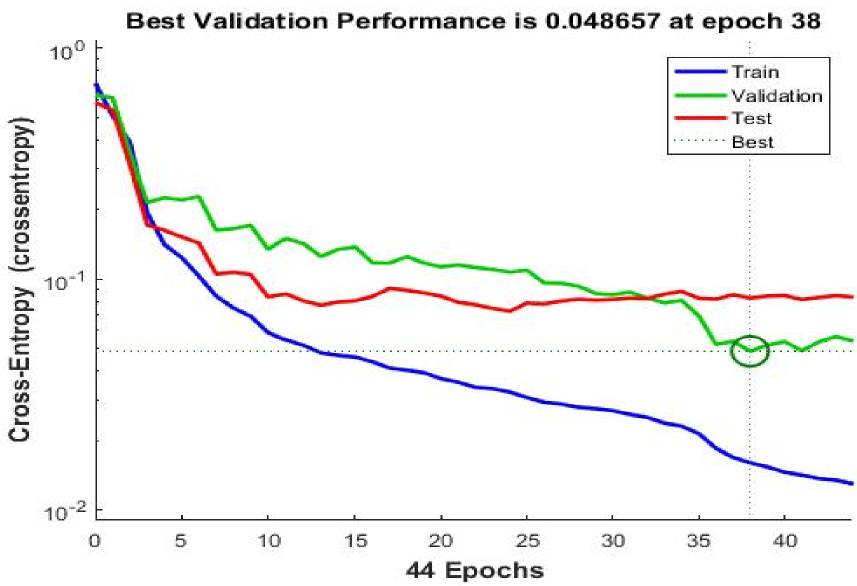

Fig. 4. Performance plot

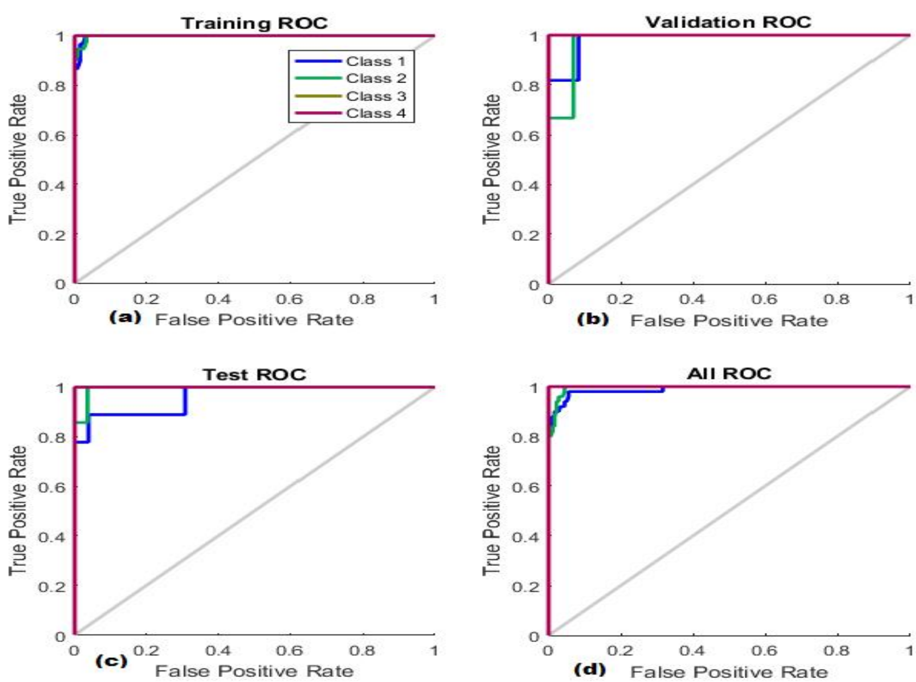

Fig. 5. Receiver operating characteristics plot

To further assess the effectiveness of the classifier, samples of leaves used for the training and those not use for the training were used to test the designed neural network. The table below depicts the result obtained.

From Table 1, it's evidently clear that the Neural Network trained to detect the ripeness of soya bean has accurately detected the ripe leaves and those that are not.

Table 1. Result of testing the classifier with different samples

S/N	Samples not used for training		Samples used for training	
	Category of leave	Correctly classified	Category of leave	Correctly classified
1	Not ripe	Yes	Not Ripe	Yes
2	Not ripe	Yes	Not Ripe	Yes
3	Not ripe	No	Not Ripe	Yes
4	Not ripe	Yes	Not Ripe	Yes
5	Not Ripe	Yes	Not Ripe	Yes
6	Ripe Ready	Yes	Ripe Ready	Yes
7	Ripe Ready	Yes	Ripe Ready	Yes
8	Ripe Ready	Yes	Ripe Ready	Yes
9	Ripe Ready	Yes	Ripe Ready	Yes
10	Ripe Ready	No	Ripe Ready	Yes

6. CONCLUSION AND RECOMMENDATION

In this research, a model for detecting the ripeness of soya beans plant has been developed. The developed model consists of three phases, pre-processing (including image acquisition, conversion and enhancement), feature extraction (colour and texture) and classification (using Artificial Neural Network). From experimental results, the simulation model shows a recognition rate of 95.7%. Though the use of soya beans differs around the globe, predicting the ripeness period of soya beans will also help reduce losses, so that prompt an action can be taken. However, implementing this technique would help in preventing losses, but a graphical user interface (GUI) will be more appropriate and ease of use for the users.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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