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NON-DESTRUCTIVE SELECTION OF FRESH OKRA USING IMAGE PROCESSING TECHNIQUE AND ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Okra (Abelmoschus Esculentus) has high nutritional value especially when consumed fresh. However, non-destructively selecting fresh okra remains a challenge, especially for farmers in Nigeria. This affect the value of the commodity and buyers on the other hand do not have complete value for what they paid for. Therefore, this research work, in the light of precision agriculture (which aims at effectiveness and efficiency in the production and cultivation agricultural product) used image processing technique for the acquisition and pre-processing of the images of okra pods/fruits, and then developed a neural network classifier for non-destructive selection of fresh okra. The developed classifier which was trained, validated, and tested with one-hundred-and-fifty (150) samples of completely fresh, matured, and over-matured; performed with an accuracy of about ninety-eight percent (98.3%). Other aspects where precision agriculture could be applied should be research for its benefits.

INDEX TERMS: *Okra, non-destructive, Image processing, neural network*

INTRODUCTION

Artificial intelligence computing tools have successfully been applied to solve diverse problems in different areas of life. Tools such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Fuzzy Logic (FL), and Neural Networks (NN) are some of the most often used tools in supervised and unsupervised learning area of computational intelligence (Hagan, et al., 2009; Das & Sreedhar, 2012).

Unsupervised learning model develops an underlying structure or distribution of input data in other to learn more about the data. That is, there are no targets used for the learning. Supervised learning, on the other hand, develops an underlying structure or distribution of input data based on known targets. That is, the input data is mapped to the targets (Brownlee, 2016). Supervised learning has found wider applications in the area of precision agriculture.

Precision agriculture is concerned with effectiveness and efficiency using information technology tools such as the SVM, NN, KNN, etc. for the purpose of ensuring profitability, sustainability, and environmental protection. It involves observation, measurement, and responding to inter and intra-field variability in plants; thus, the suitability of using supervised learning model to address problems in the area (McBratney, et al., 2005; Chris, 2014).

One of the areas of precision agriculture that has gained much attention of researchers in the recent is the prediction of ripeness, maturity, or freshness of crops or fruits (Llobet, et al., 1999; Rahman, et al., 2009; Mustafa, et al., 2010; Susilawati, et al., 2012; Bakar, et al., 2013; Alfatni, et al., 2014). This is because harvesting at the appropriate time reduces wastage and enhances the economic importance of plants and their yields. For example, harvesting maize at optimum maturity does not only reduce wastage but the leaves and stalk of the plant which still contain higher nutritional content can be used to feed cattle (Peter, et al., 2017).

Although there has been a lot of research to determine the ripeness, maturity or freshness of plants' yields, there is still need for much to be done as has not been satisfactory results or a one solution fit all cases breakthrough. That is, no single tool has been implemented to be able to determine the maturity, ripeness, or freshness of all plants' yields due to the difference in either color, size, biological classification, or other geometrical attributes of the yields. Therefore, this research seeks to make use of image processing techniques and artificial neural network to determine the freshness of an okra plant.

Okra which is also known in English as lady's fingers, gumbo; in India as gombo, bendakai, bhindi; in Malay as Kacang bendi; and in Spanish as quimgombo; and it is known scientifically as Abelmoschus Esculentus or Hibiscus Esculentus (McWhorter, 2000). It is a common pod vegetable and nightshade vegetable used in making soups, Cajun, and Creole cuisines. Research shows that okra has a lot of nutritional benefits since it contains vitamin A, B6, C, high fiber, folic acid, magnesium, potassium, calcium, iron, etc. It also has health benefits as it improves eyesight, lowers cholesterol, stabilizes blood sugar, aids digestion, etc. (Gemede, et al., 2015). Okra also serves as a cash crop to farmers especially those in Nigeria. Therefore, it can be asserted that contributes to the Gross Domestic Product (GDP) of a nation.

From the nutritional and health benefit perspective, Okra is said to be most useful when consumed fresh. Therefore, buyers are more persuaded when it fresh. However, determining which okra fruit is fresh or otherwise is very difficult since most persons rely on the color (which is subjective and depends on the species), or they have to they have to cut through it to find out if it is fresh or not. Cutting through it could lead to the Okra being affected by diseases and thus, wastage results. Therefore, a non-destructive way of determining an under-fresh, fresh, and over-matured okra fruit becomes necessary. To achieve this, image processing technique is used for the extraction of data and neural network is used for the classification due to its suitability and superiority in supervised learning.

MATERIALS AND METHODS

Okra Pods (Fruits) and Image Acquisition

Okra fruits are pentagonal and capsule-like containing numerous seeds which are round in nature. It is usually between three to seven inches (3.0" - 7.1"). The plant is usually two meters (2m) with leaves hearty in shape and three to seven inches long and broad. The okra fruit may be green or red. However, the popular one is the green shown in Figure 1 is used for this research.

Figure 1: Okra Pod/Fruit

The camera used for the image acquisition is a Panasonic Full High Definition (1920X1080p) Intelligent 50X Zoom with 32.4 mm wide optical zoom video camera which is a Charge-Couple Device (CCD). This choice is influenced by the fact that CCD cameras are often used in applications that involves image processing. Also, CCD cameras are known to capture images of higher quality and have lower noise. They have the highest light sensitivity of any light detection available, higher dynamic range, quantum efficiency, and best dark signal (Karim, et al., 2006). Since images captured by CCD cameras have lower noise, there will be no need for any enhancement of the image as a pre-processing task. However, image cropping is done to have a sizeable image for the processing.

A random sampling approach was used to select one hundred and fifty (150) okra fruits for the image acquisition, fifty (50) samples each of the three (3) freshness levels. The three freshness levels are referred in this research as "Completely Fresh", "Matured", and "Over-Matured". The completely fresh category is when the okra fruit is still very tender and said to contain highest nutrient value; it is usually between one to three inches (1" – 3"). The matured category is between when the okra fruit is beginning to lose its nutrients and when it begins losing its green pigment; thus, its nutritional value is said to start degrading; it is usually between three to five inches (3" to 5"). The over-matured category is between when the okra fruit starts losing its green pigment to when it completely lost it; it is said to be dried and may only be harvested for seed purpose since it has the lowest level of nutrient; it is usually between five to seven inches (5" – 7").

Selection/Classification of Okra Fruit

Having acquired the images and cropping them such that only the portion of the okra fruit is in the image, color and texture attributes are retrieved from the image for the purpose of classification. This is because using color and texture features often gives a better result than using either color or texture features only (Asha, et al., 2015). The texture attributes were retrieved using the Gray Level Co-Occurrence Matrix (GLCM) was used due to its reported effectiveness in other similar research; the color attributes were retrieved using the Human Saturation Value (HSV) color model since it preserves the quality of an image during pre and post-processing (Rafael & Richards, 2008; Dayanand, 2012; Garima, 2014; Pratap, et al., 2014).

Having retrieved these attributes, a neural network model made of twenty (20) neurons in the hidden layer as shown in Figure 2 was trained, tested, and validated for the purpose of predicting the freshness class of a given okra fruit. The training phase of the network helps it to adjust its errors accordingly until an acceptable error is attained. Training this network, seventy percent (70%) of the samples making one hundred and four (104) was used. The validation phase is used to measure the network's generalization while training the network. Thus, it helps to specify when the network should stop training when generalization of the network stops improving. For this, fifteen percent (15%) which is twenty-three (23) samples were used. The testing phase assesses the network performance. For this also, twenty-three (23) samples which is also equivalent to fifteen percent (15%) of the samples were used.

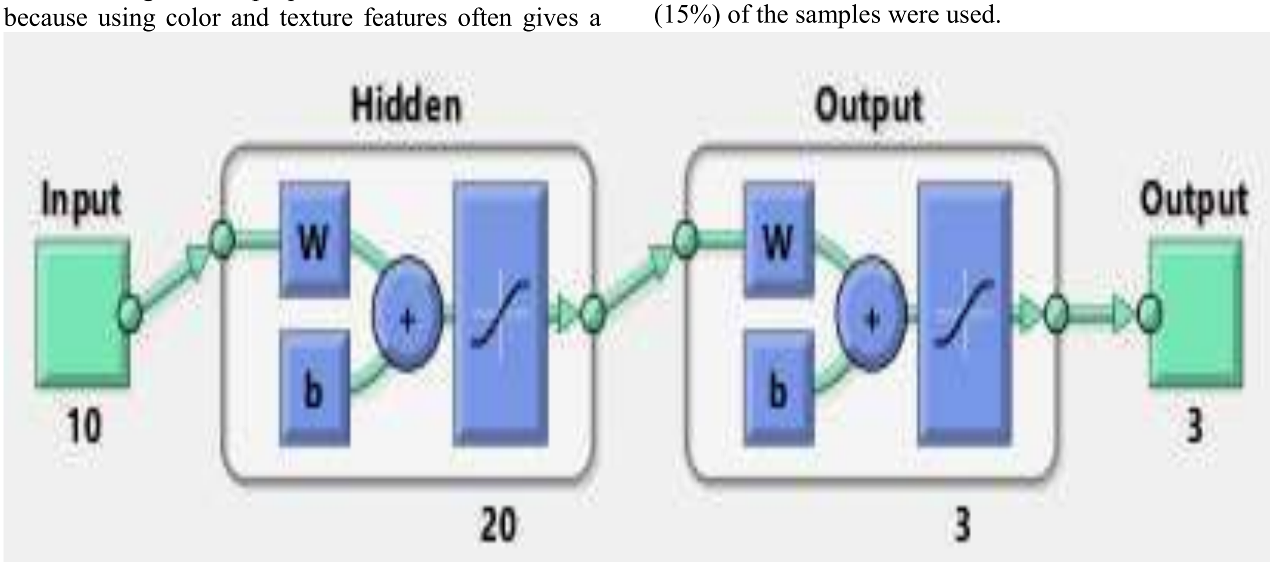

Figure 2: Neural Network Model

RESULTS AND DISCUSSIONS

The results of this research are presented in terms of confusion matrix, receiving operating characteristics, error histogram, and performance plots.

In Figure 3 where the classification confusion matrix is presented, it is clear that the classifier performed with hundred percent (100%) accuracy of classification during the training and validation phases. However, at the test phase, the classifier performed with about eighty-eight percent (88.9%) accuracy of classification. And for the complete (all) confusion matrix which specifies the overall performance of the classifier, an accuracy of about ninety-eight percent (98.3%) is achieved.

In Figure 4 where the classification receiving characteristic is presented, for the training phase, the plots are set to be one (1) on the true positive rate axis, for the validation and test phases, the plots tend towards one(1) on the true positive rate axis of the curves. And for the complete (all) receiving operating characteristics, the plots are more tending towards one (1) on the true positive rate axis

Figure 3: Classification Confusion Matrix

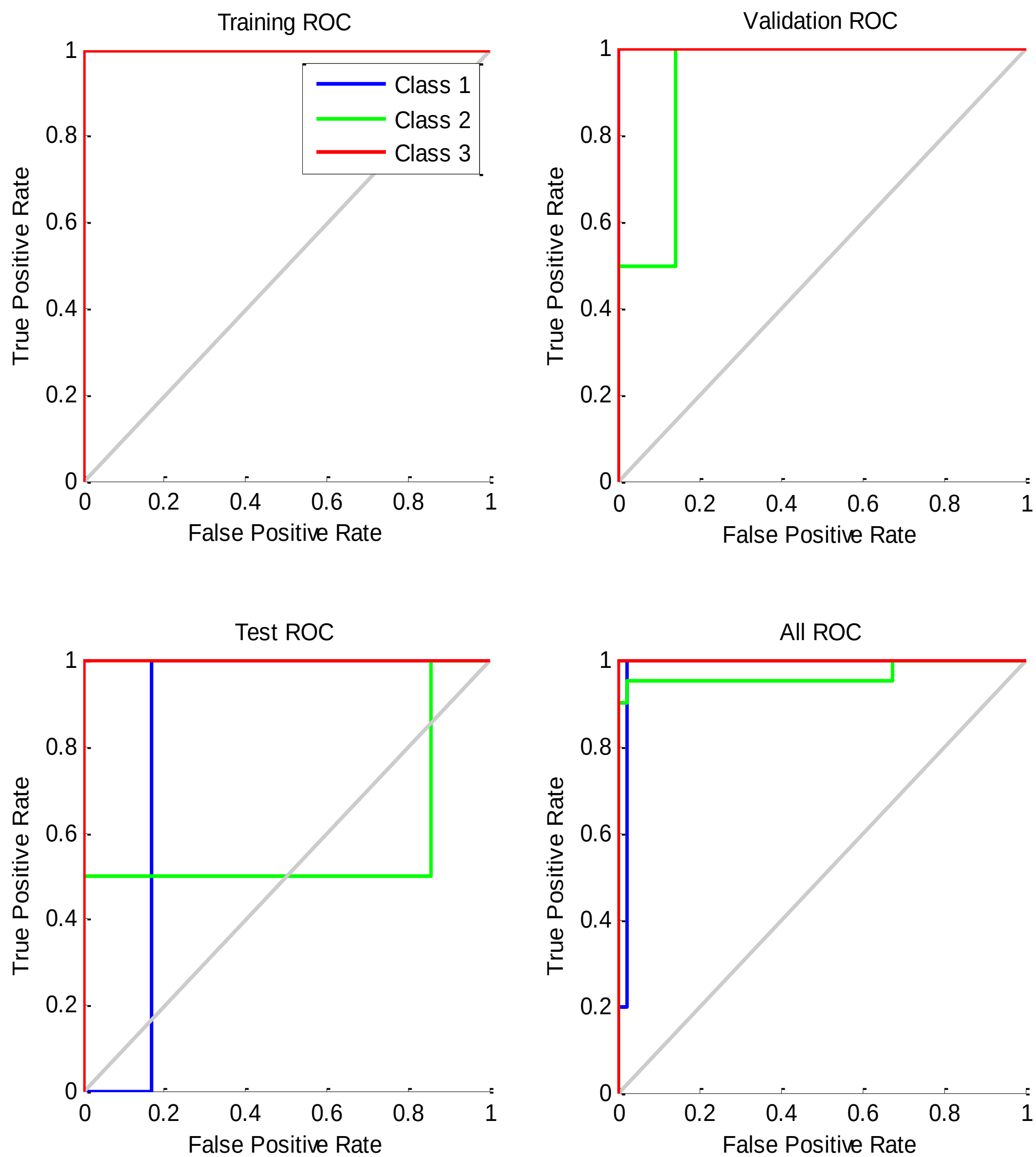

Figure 4: Classification Receiving Operating Characteristics

In Figure 5, the Performance Plot of the classifier is presented. At epoch 49, the plots for the training, validation, and test tend to converge at the best fitting plot. This implies a desirable performance of the neural network classifier.

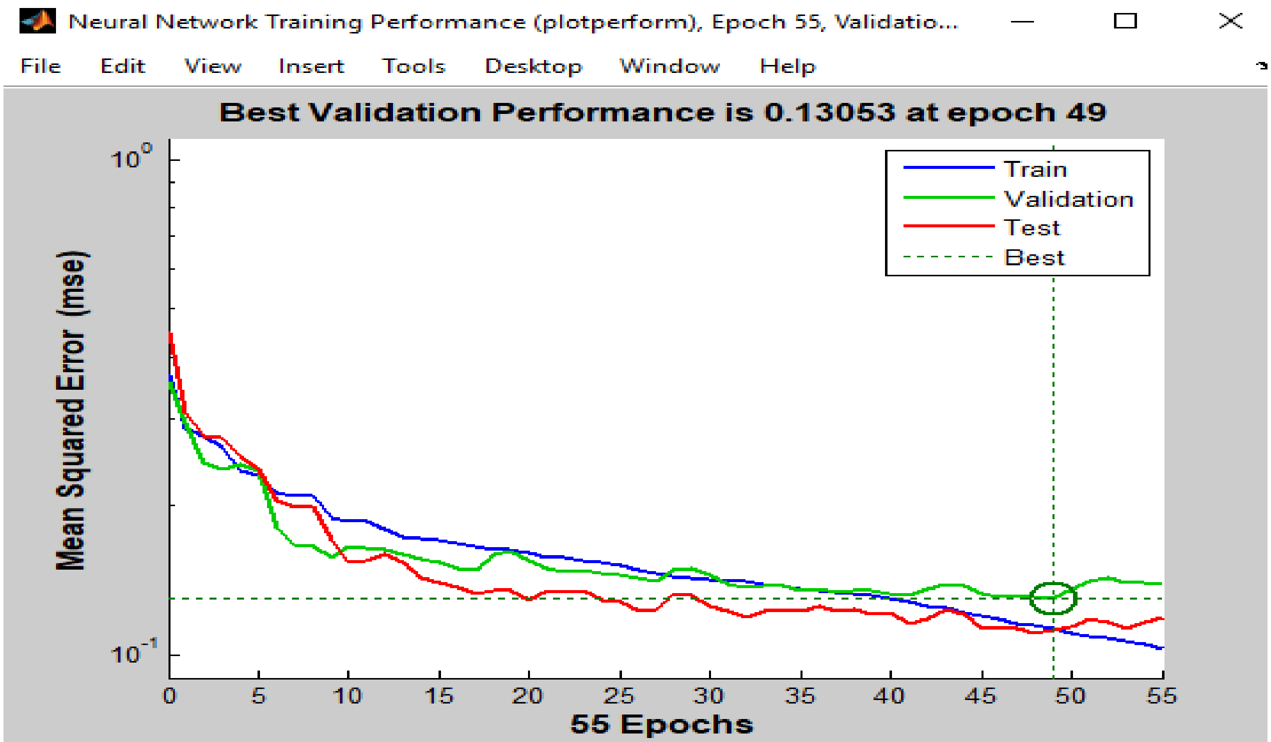

Figure 5: Classification Performance plot

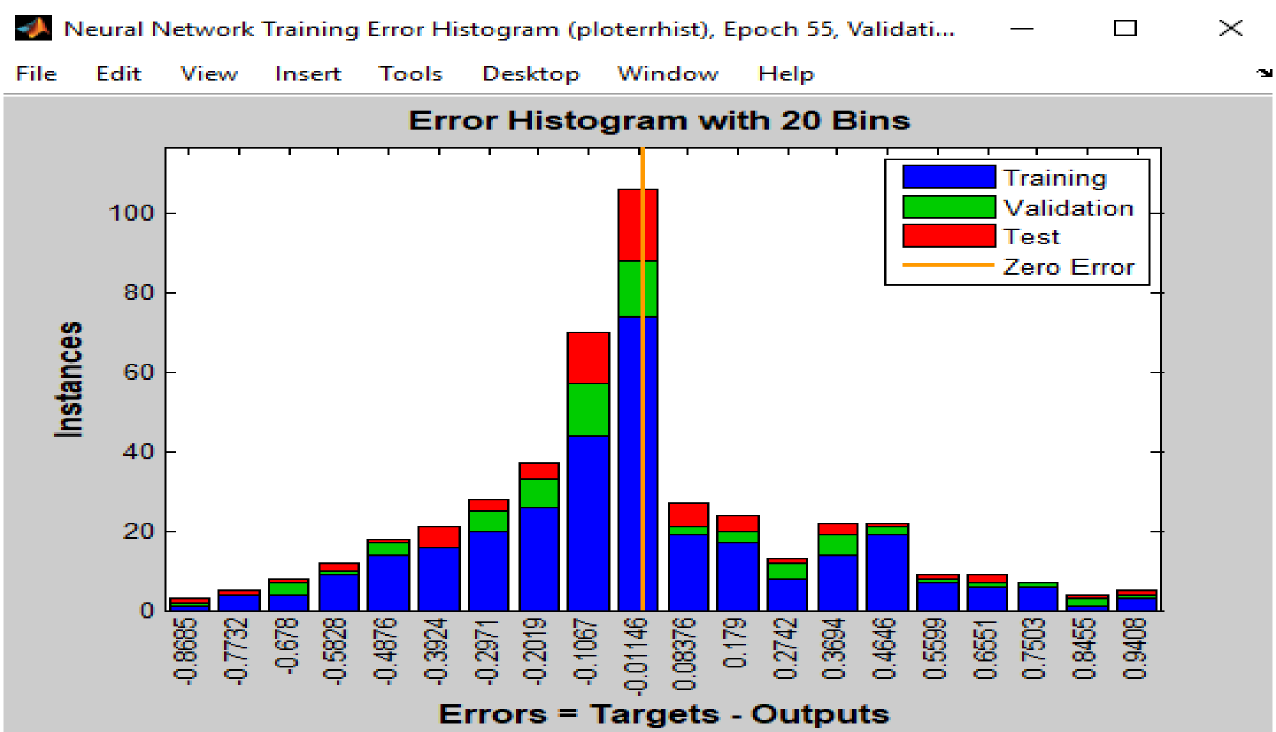

Figure 6: Classification Error Histogram

In Figure 6, the Classification Error Histogram is presented. It is clear that the classifier performed very remarkably at the classification of okra fruits since the values tended to zero (0). The error distribution is such that it is symmetrical about the zero error line in the plot.

CONCLUSION

Following the nutritional benefits of fresh okra, one can assert that it is in high demand. However, ensuring that it is adequately fresh cannot be guaranteed (especially with Nigerian farmers). Therefore, the need for a tool to effectively select fresh okra without causing any defect becomes a necessity. This research developed a neural network classifier which achieves the goal of non-destructive selection of fresh okra at about ninety-eight percent (98.3%). The implication is that the market value of this commodity can be ensured since the buyer is certain (up to 98.3%) that the okra being paid for is completely fresh and thus, has higher nutritional value so desired.

This research has demonstrated the application of computational intelligence tool in the realization of precision agriculture where fresh okra can be selected without and destruction of the fruit. This can be practically achieved when the classifier is integrated into a device that may be used for the classification. Such a device could be a smartphone with the ability (API) to implement neural network codes.

From this researcher, we see the potential of extending this work such that other computational intelligence tools such as fuzzy logic, genetic algorithms, SVM, KNN, etc. could be used for the detection and classification of Okra. These approaches may be compared to determine which tool has a better result. Also, the aspect of detection of diseases in okra has not received much attention, thus, this is another area that could be researched.

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