Modeling Ripeness Grading of Palm Oil Fresh Fruit Bunches through Image Processing using Artificial Neural Network

Osama M. Ben Saaed[1], Meftah Salem M Alfatni[1,2]*, Abdul Rashid Mohamed Shariff[3] and Hadya S Hawedi[1]

[1]Faculty of Information Technology, Al-Asmarya Islamic University, Zliten, Libya,
[2]Faculty of Information Technology, Elmergib University, AL-Khomes, Libya,
[3]Faculty of Engineering, Universiti Putra Malaysia, 43400, Serdang, Selangor, Malaysia.
Faculty of Information Technology, Al-Asmarya Islamic University, Zliten, Libya;

Abstract

This research introduces the use of a hyperspectral based system to detect the ripeness of oil palm fruit bunches (FFB). FFB are scanned by a hyperspectral device and the reflectance recorded for different wavelengths. A sample of 209 fruits from one type of oil palm fresh fruit bunches (*Nigrescens*) iscollected for categorization using the over-ripe, ripe and under-ripe categories. Attribute of the fruit in the visible and near-infrared (400–1000 nm) wavelength range regions is measured. An artificial neural network(ANN)classified the different wavelength regions on oil palm fruit by pixel-wise processing. ANN is employed, and the trained network is integrated back into the system to allow oil palm fruit ripeness differentiation. The results are then compared to classifications made by a trained human grader. The developed ANN model successfully classifies oil palm fruits into three ripeness categories. A comparison of the accuracy of results between ANN approach and the conventional system that applies a manual classification is made. The results show that ANN approach yields more than 90% classification accuracyfor all three categories. The findings of this research will help increase the efficiency of quality harvesting and grading of fresh fruit bunches (FFB).

Keywords: hyperspectral, ripeness, oil palm fresh fruit bunches, color, visibility, near infrared, classification.

1. Introduction

Its global consumption contributes to uses both in the food and non-food sectors, including the biofuel industry (Shazana et al., 2018). In 2016, Palm Oil Analytics provided statistics of the top 10 palm oil producers per country. Figure 1 reflects the top global palm oil producers are Indonesia and Malaysia, contributing 58% and 29% respectively ("Essential Palm Oil Statistics Palm Oil Analytics," 2017).The growth of the world population increased the demand for production of palm oil. Palm oil is advantageous over other oil types because of its lower cost and being free from trans-fatty acids properties(Khatun, Moniruzzaman, & Yaakob, 2017), (Jafari, Othman, Witzke, & Jusoh, 2017).

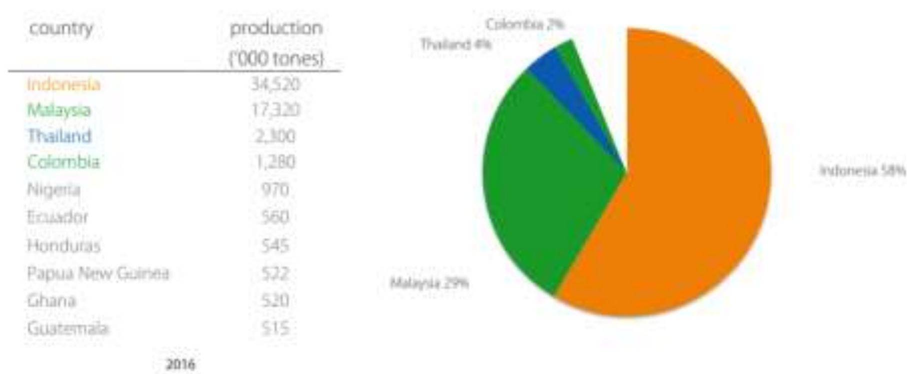

Figure 1 Top 10 Palm Oil Producers by Country 2016

Statistics indicate that there is an increasing need in the production of palm oil to meet global demand. Malaysia as the second producer of the world, of crude Palm Oil has increased its production overtime since 1984(“Essential Palm Oil Statistics Palm Oil Analytics,” 2017), as shown in Figure 2.

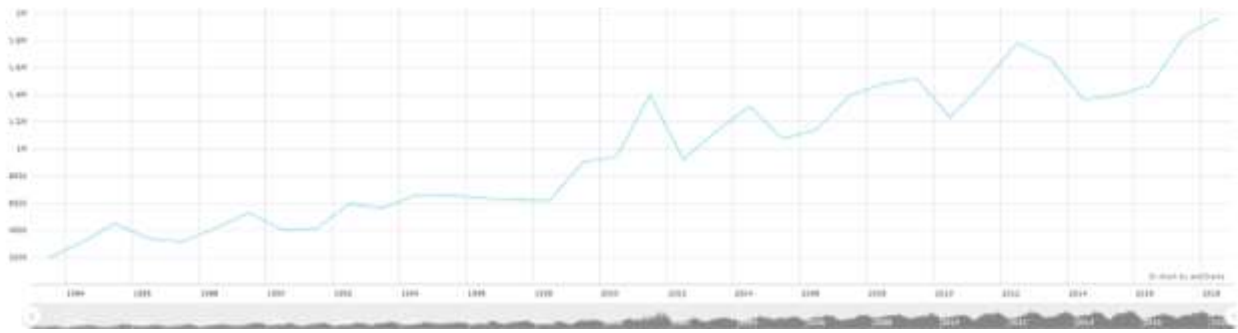

Figure 2 Crude Palm Oil Production - Malaysia

2. Related Literature and Studies

2.1 Machine Vision

Machine vision (MV) is the technology and methods used to provide imaging-based automatic inspection and analysis for such applications as automatic inspection, process control, and robot guidance, usually in industry as shown in figure 3. It is a term encompassing a large number of technologies, software and hardware products, integrated systems, actions, methods and expertise. It attempts to integrate existing technologies in new ways and apply them to solve real world problems. Definition varies but all include the technology and methods used to extract information from an image on an automated basis, as opposed to image processing, where the output is another image. The information extracted can be a simple good-part/bad-part signal, or more a complex set of data such as the identity, position and orientation of each object in an image. The information can be used for such applications as automatic inspection and robot and process guidance in industry, for security monitoring vehicle guidance and in agriculture(Nandi et al., n.d. 2000)(Alfatni, Shariff et al. 2011; O. M. B Saeed, S Sankaran et al. 2012; Alfatni, Shariff et al. 2013)(National & Ceres, 2013).

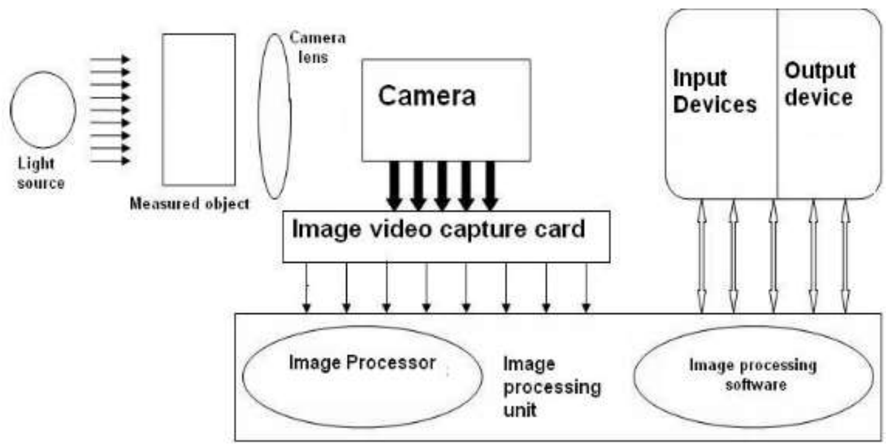

Figure 3 Machine Vision in Agriculture

2.2 Image Processing

Digital image processing, also referred to as computer imaging, can be defined as the acquisition and processing of visual information by computer. Image processing is looking beyond the input which is raw image data and finding information needed through the process of image segmentation, image transforms, and feature extraction (Oak, 2016)(Alfatni, Shariff et al. 2014).

2.2.1 Image Segmentation.

Image segmentation is the division of an image into disjoint regions according to characterization of the image within or in-between the regions. Image segmentation then is dividing the domain of the image into relevant components One of the most common used algorithm is the Mean Shift Segmentation. The mean shift technique is one of many techniques under the heading of "feature space analysis" and is widely used in the vision community. It is made up of two basic steps: a mean shift filtering of the original image data (in feature space), and a consecutive clustering of the filtered data points (Pantofaru, 2005).

Given n data points x_i in *d*-dimensional space. The general multivariate kernel density estimator with kernel *K(x)* is defined as

$$\hat{f} - \frac{1}{n}\sum_{i=1}^{n} K_H\,(x - x_i)$$

Equation.1

The radially symmetric kernel with the identity matrix $H - h^2 l$, on Equation (1) can be rewritten by

$$\hat{f} - \frac{1}{nh^d}\sum_{i=1}^{n} K\,\frac{(x - x_i)}{h}$$

Equation.2

By taking the gradient of Equation 2 and applying some algebra, a mean shift vector can be obtained by:

$$\boldsymbol{m}(x) = C\frac{\nabla \hat{f}(x)}{\hat{f}(x)}$$

Equation.3

where *C* is a positive constant and

$$\boldsymbol{m}(x) = \frac{\sum_{i=1}^{n} x_i g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)} - x$$

Equation.4

The function$g(x)$ is the derivative of the kernel profile *k(x)*, i.e., $g(x) = -k'(x)$.

Generally, the function kernel $K(x)$ is often broken into the product of two different radially symmetric kernels namely, the spatial domain and the color range.

2.2.2 Image Transforms

There are different types of image transforms, one example is the Fourier Transform where the input image is the spatial domain and the output of the transformation is the frequency domain. This type of transform breaks the image down into its sine and cosine components. Transform can be used in image analysis, image filtering, or image compression. Image transforms are often linear and are represented by the transform matrices ***A*:**

$$\boldsymbol{X}=\boldsymbol{A}\boldsymbol{x}$$

Equation.5

Where***x*,*X***are the original and transformed image, respectively. In most case, the transform matrices are unitary.

$$A^{-1} = A^{\cdot T}$$

Equation6

The columns of $A^{\cdot T}$ are the basis vectors of the transform. In the case of two-dimensional transforms, the basis vectors correspond to the basis image (Mademlis, Tefas, Nikolaidis, & Pitas, 2017). The algorithm used in most image transforms are the Discrete Fourier Transform (DFT) and the Discrete Cosine Transform (DCT). According to Pitas, the DFT has very interesting theoretical properties and is widely used in digital filter implementations and in power spectrum estimation. The DCT however, is used in transform image coding schemes for it is an excellent tool for digital image compression (Mademlis et al., 2017).

2.2.3 Feature Extraction

Feature extraction is known as changing an input image or a data into a significant number of features. If this process is done with care then significant set of features can be extracted quickly from the large data (Ansari, 2016)(Alfatni, Shariff et al. 2013). One of the most commonly used process in feature extraction is edge detection.

An edge is detected when there is a huge contrast between image pixels also stated that convolution is often used to provide an edge filter that takes in a grayscale image and yields a binary image whose 1-valued pixels are meant to represent an edge within the original image.

2.3 Hyperspectral imaging system (HIS)

Existing studies report that optical sensing and imaging technologies such as machine vision and spectroscopy are considered as an effective tool for nondestructive inspection and post- harvest fruit quality, safety detection, sorting, and process automation(Khodabakhshian & Emadi, 2018)(Li, Emr, Malling, & Me, 2018)(Harun et al., 2013)(Mohammed et al., 2012). Machine vision has success in categorizing fruits with respect to size, color, and other appearance indices. However, its capacity for determining internal quality of fruits is limited. Hyperspectral imaging system addresses this limitation. hyperspectral imaging (HSI) has emerged as a nondestructive, noncontact, and nonconventional technique that integrates two mature technologies of conventional imaging and spectroscopy to provide both spatial and spectral information simultaneously. The hyper- spectral images form a three-dimensional hyperspectral cube known as "hypercube," which is composed of two-dimensional spatial image and one-dimensional spectrum. Therefore, HSI is capable of representing both physical and chemical attributes by analyzing the image features and performing predicting model using the spectral information, respectively. The technique was also applied to detect the ripening process of fruits such as strawberry, peach, banana, and tomato, which showed a potential use of hyperspectral imaging for the fruit's ripeness/quality assessment.

HSI generates a three-dimension imaging cube with images at a range of continuous wavelengths. A single spectrum can be extracted from each individual pixel representing the absorption properties and the textural information of fruit samples.

Similar with traditional visible imaging and spectroscopic methods, HSI is non-destructive and requires little sample preparation, but it is advantageous in that it can record both spatial and spectral information simultaneously. For the assessment of fruit quality, two types of wavelength dispersion devices are normally used i.e., line scanning and area scanning coupled with an imaging sensor for the HSI image acquisition (Li et al., 2018)(Saeed, Shariff et al. 2013).

2.4 Neural Network

It is said that neural networks (also known as Artificial Neural Networks, ANN) essentially modeled on the parallel architecture of animal brains, not necessarily human ones. Also, the network is based on a simple form of inputs and outputs. This is further exemplified by Dr. Robert Hecht-Nielson’s definition of a neural network (as quoted in “Neural Network Primer: Part I” by Maureen Caudill, AI Expert, Feb. 1989), “...a computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs.”.

To illustrate what a neural network is, states, “In biology terms, a neuron is a cell that can transmit and process chemical or electrical signals. The neuron is connected with other neurons to create a network; picture the notion of graph theory with nodes and edges, and then you’re picturing a neural network.”

3. Materials and Methods

Figure 4 reflects the methodology used in the conduct of this study.

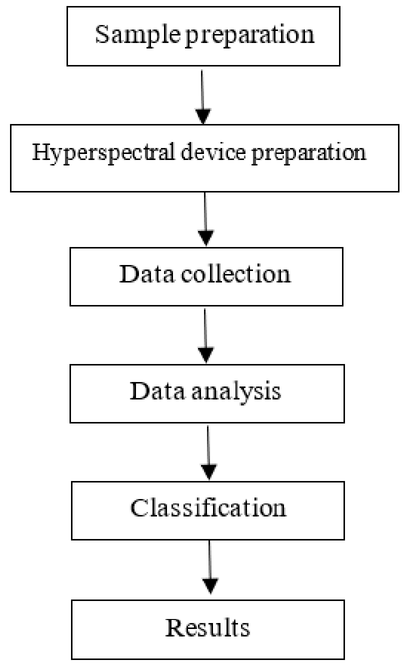

Figure 4 Research Method

3.1 Sample Preparation

Colors of oil palm fruits were classified into six classes: black, hard, ripe, overripe, empty, and rotten bunch. Table 1 shows the standards established by the Malaysian Palm Oil Board (MPOB). This study classified oil palm fruit bunch into three categories of ripeness - ripe, under ripe, and over ripe. 209 bunches evaluated by inspectors were allocated for testing and divided into three groups, with each group having 108 bunches of FFBs. The categories were determined qualitatively by human expert. Table 1 reflects the palm oil FBB categories. All the samples were freshly taken from MPOB farm area in Kluang/Johor, Malaysia, a tropical farm. This study selected Elaeisguineensis from Nigrescens type as a sample because it is commercially used in

Malaysia. All fruits of the same bunch are in similar status of ripeness although the fact that their colors and sizes may vary with locations on the bunch (Abdullah et al., 2001).

Table 1. Palm Oil FBB Categories

Category	Description
Black	Bunch with complete fruits
Hard	Bunch with 1 to 9 fruits detached
Ripe	Bunch with 10 %to 50 % fruits detached
Over ripe	Bunch with 50% to 90% fruits detached
Empty bunch	Bunch with more than 90% fruits detached
Rotten	Bunch with all or part having turned black

3.2 Hyperspectral device preparation

The hyperspectral active sensor system (as shown in Figure 5) was used for data collection. Image acquisition device utilized for this study is simply composed of a high resolution (1600x1200 pixels), with a pixel depth of 12 bits/pixel with 824 spectral bands ranging from 400 to 1000nm. The hyperspectral imaging system technology on line-scan mode (called pushbrom mode) technology for determining ripeness of FFB is still under study because it is determined by the color of FFB even though other factors (i.e. the maximum oil content produced, the number of loose fruits seen on the ground and the right stage of maturity in harvesting oil palm fresh fruit bunches (FFB)) are critical to ensure optimum quantity of oil production and quality, and in the long run the productivity of the industry (WanIsmail et al., 2000).

The reflectance measurements were analyzed. The hyperspectral imaging system was employed in this research to allow different configurations for imaging in the visible-NIR range (400 – 1000 nm).

Figure 5 Schematic view of the hyperspectral imaging system showing the bunch on the conveyor

3.3 Data Collection

Figure 6 shows samples of FFBs classified according to three groups based on the standards established by Malaysian Palm Oil Board (MPOB): 'Underripe' with 1 to 9 fruits detached from the bunch, 'Ripe' with 10-50% fruits detached from the bunch and 'Overripe' with 50-90% fruits detached from the bunch.

Figure 6 Typical image of Nigrescens oil palm fruit

In this study, spectral reflectance data were collected from 209 oil palm fresh fruit bunches, with representative samples.FFBs were categorized into above mentioned classes by the certified inspectors prior to the data collection.

4. Data Analysis

The replicates for each sample were based on average computed prior to further analysis. Matlab® (ver. 7.6, The MathWorks Inc., Natick, MA) was used for the analysis of the spectral data.

4.1 Implementation of Artificial Neural Network (ANN)

209 fruits were inspected and distributed into three classes, with 70 fruits for each class, and separated for independent training and testing data sets (75:25) to evaluate different classification algorithms. Artificial Neural Network (ANN) is designed to

classify the results into the observed three categories of ripeness using the Feed-Forward Network architecture.

4.2 Receiver Operating Characteristic (ROC) Classification

This ROC curve is an alternative to measure accuracy for the evaluation of learning algorithms on natural datasets. Key assumption of ROC analysis is that true and false positive rates describe the performance of the model independently of the class distribution. This analysis is applied to provide more robust comparative evaluation of expected performance on target data than simple comparison of error, which assumes the observed class distribution and does not reflect any differences in the cost of different types of error. ROC analysis might be of value for evaluating expected classifier performance under varying class distributions.

Further, ROC curves describe the predictive behavior of a classifier independent of class distributions or error costs, so they decouple classification performance from these factors (Provost and Fawcett, 1997).ROC analysis is often called the ROC Accuracy Ratio, a common technique for judging the accuracy of default probability models.

4.3 Area under ROC Curve (AUC)

Area under Roc Curse (AUC) is a probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one (Fawcett, 2006). AUC is also a significant measure of the accuracy in the detecting the ripeness test: if this area is equal to 1, then ROC curve consists of two straight lines - one line is vertical from (0, 0) to (0, 1) and the next line horizontal from (0, 1) to (1, 1). This test is

100% accurate for both the sensitivity and specificity are 1.0, therefore having no false positive and no false negative. Thus, a test that cannot distinguish between normal and abnormal corresponds to an ROC curve which results to a diagonal line from (0, 0) to (1, 1). ROC area for this line is 0.6. ROC curve areas are typically between 0.6 and 1.0. Consequently the value of AUC will always satisfy the following inequalities of $0 \leq AUC \leq 1$, with an AUC close to 1 (i.e. area of unit square) indicating a very reliable diagnostic test.

5. Results

The distinctive reflectance in oil palm fruit in three categories fell within the wavelength range of 400-1000 nm. But with the application of ANN, the study revealed that an area from 800 nm to 900 nm can generate data distinguishable among the three layers (Figure 7). The ripeness categories can be best differentiated between 800 nm to 900 nm. In contrasts, the range of 400 nm to 700 nm (i.e. the UV region), could not distinguish the ripeness categories.

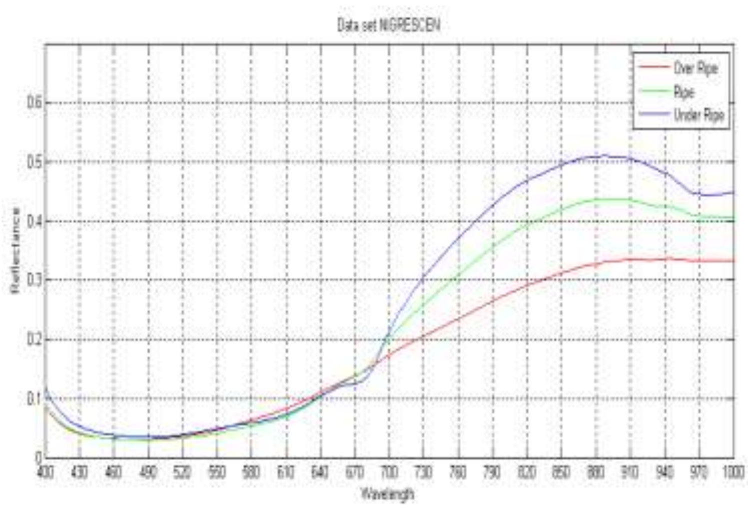

Figure 7 Distinguishing reflectance in oil palm fresh fruit in three categories

5.1 Training Stage

The 209 fruits were inspected and distributed into three classes of underripe, ripe and overripe. These samples were randomized and separated for independent training and testing datasets (75:25) to evaluate different classification algorithms. The training and testing datasets were comprised of 156 and 53 samples respectively.

While training dataset was used to train the algorithm, testing datasets were used to test the developed (trained) algorithm in predicting the class of the test dataset samples. Classification accuracies were determined in specific features which were extracted from reflectance data and were used in the classification algorithm. Threshold method was used to determine which bunch belongs to which class and to assign the deferent intervals to each class based on reflectance values. The error margin selected for training was set at 0.0001. under-ripe, ripe and overripe. Target classes were set at 1,0,1 respectively; however, the ANN-model output in black line can not fit the target during the training stage as shown in Figure 8.

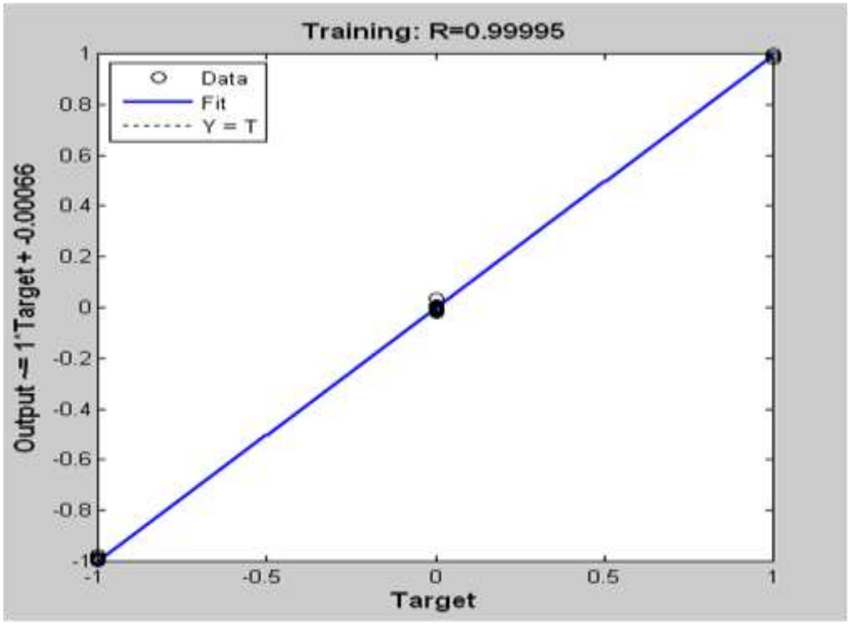

Figure 8 Training step of ANN-MLP

5.2 Testing Stage

The remaining 25% of the total samples of bunches were used for testing with input data for over ripe set at< - 0.7 where classes belonged under target -1, ripe class at -0.7 < 0.7 where classes belonged under target 0, and under ripe at > 0.7 where classes belongedunder target 1.

5.3 ROC classification

Figure 9 shows the ROC curve and the AUC result. The ANN-MLP classifier illustrates great performance results that acquire an AUC equal to 0.9454 for adaptive gain factor classification in three categories of Nigrescens type. This result strengthens positive performance results from the proposed algorithm.

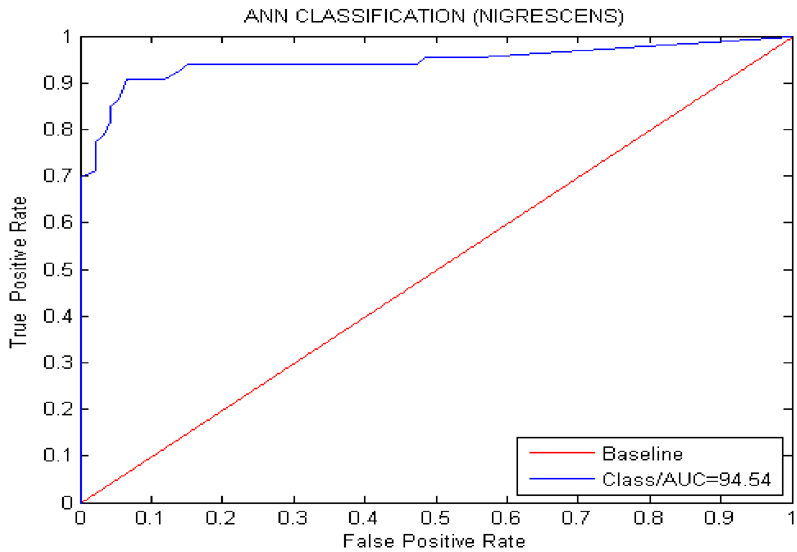

Figure 9. AUC tasted from the ROC curve by using ANN (Nigresences)

6. Conclusion

This studyproposes a new approach for detecting the ripeness of FFBs by using supervised machine learning classifier, the ANN method. ANN classifier implements and comparesresults to determine a high accuracy rate of ripeness of the FFBs using the ROC and AUC.

The results show that oil palm fresh fruit bunch ripeness detection system using a hyperspectral and ANN classifier give a high accuracy rate of 94.54%, indicating that Artificial Neural Network (ANN) successfully classifies the ripeness level of the fruit bunches.

References

Abdullah, M.Z., Guan, L.C., and Mohd. Azemi, B.M.N. 2001. Stepwise discriminant analysis for colour grading of oil palm using machine vision system. Transactions of Institution of Chemical Engineers, 79, 223-231.

Ansari, M. D. (2016). Feature Extraction Method for Digital Images Based on Intuitionistic

Fuzzy Local Binary Pattern, 345–349.

Essential Palm Oil Statistics Palm Oil Analytics. (2017).

Harun, N. H., Misron, N., Sidek, R. M., Aris, I., Ahmad, D., Wakiwaka, H., & Tashiro, K. (2013). Investigations on a Novel Inductive Concept Frequency Technique for the Grading of Oil Palm Fresh Fruit Bunches, 2254–2266. https://doi.org/10.3390/s130202254

Ismail, W.I.W., Bardaie, M.Z., and Hamid, A.M.A. 2000. Optical properties for mechanical harvesting of oil palm FFB. Journal of Oil Palm Research, 12 (2), 38-45.

Jafari, Y., Othman, J., Witzke, P., & Jusoh, S. (2017). Risks and opportunities from key importers pushing for sustainability : the case of Indonesian palm oil. https://doi.org/10.1186/s40100-017-0083-z

Khatun, R., Moniruzzaman, M., & Yaakob, Z. (2017). Sustainable oil palm industry : The possibilities, *76*(March), 608–619. https://doi.org/10.1016/j.rser.2017.03.077

Khodabakhshian, R., & Emadi, B. (2018). Application of Vis / SNIR hyperspectral imaging in ripeness classification of pear. *International Journal of Food Properties*, *20*(3), 3149–3163. https://doi.org/10.1080/10942912.2017.1354022

Li, B., Emr, N., Malling, E., & Me, K. (2018). Advances in Non-Destructive Early Assessment of Fruit Ripeness towards Defining Optimal Time of Harvest and Yield Prediction — A Review, 1–20. https://doi.org/10.3390/plants7010003

Mademlis, I., Tefas, A., Nikolaidis, N., & Pitas, I. (2017). Summarization of human activity videos via low-rank approximation. *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*, 1627–1631. https://doi.org/10.1109/ICASSP.2017.7952432

Mohammed, O., Saeed, B., Sankaran, S., Rashid, A., Shariff, M., Zulhaidi, H., … Hazir, M. (2012). Classification of oil palm fresh fruit bunches based on their maturity using portable four-band sensor system. *COMPUTERS AND ELECTRONICS IN AGRICULTURE*, *82*, 55–60. https://doi.org/10.1016/j.compag.2011.12.010

Nandi, C. S., Tudu, B., & Koley, C. (n.d 2000.). Machine Vision Based Techniques for Automatic Mango Fruit Sorting and Grading Based on Maturity Level and Size. https://doi.org/10.1007/978-3-319-02315-1

National, S., & Ceres, R. (2013). A Survey of Computer Vision Methods for Locating Fruit on Trees A Survey of Computer Vision Methods for Locating Fruit on Trees, (January). https://doi.org/10.13031/2013.3096

Oak, R. (2016). A Study of Digital Image Segmentation Techniques, *5*(12), 19779–19783. https://doi.org/10.18535/ijecs/v5i12.76

Foster Provost, Tom Fawcett 1997, Analysis and Visualization of Classifier Performance: Comparison under Imprecise Class and Cost Distributions

Caroline Pantofaru Martial Hebert 2005. A Comparison of Image Segmentation Algorithms

Shazana, N., Mohd, N., Rosli, R., Amin, M., Halim, A., Chan, K., … Low, E. L. (2018). PalmXplore : oil palm gene database, 1–9. https://doi.org/10.1093/database/bay095

Stewart, C. G. (2018). *A situation analysis by the IUCN Oil Palm Task Force*.

Alfatni, M. S., A. R. M. Shariff, et al. (2011). "Recent Methods and Techniques of External Grading Systems for Agricultural Crops Quality Inspection - Review." International Journal of Food Engineering 7(3): 1-40.

Alfatni, M. S. M., A. R. M. Shariff, et al. (2014). "Oil palm fresh fruit bunch ripeness classification based on rule-based expert system of ROI image processing technique results." IOP Conference Series: Earth and Environmental Science 20(1): 012 - 018.

Alfatni, M. S. M., A. R. M. Shariff, et al. (2013). "Recognition System of Oil Palm Fruit Bunch Types Based on Texture Feature and Image Processing Techniques." Advanced Science Letters 19(12): 3441-3444.

Alfatni, M. S. M., A. R. M. Shariff, et al. (2013). "The application of internal grading system technologies for agricultural products-Review." Journal of Food Engineering 116(3): 703-725.

O. M. B Saeed, S Sankaran, et al. (2012). "Classification of oil palm fresh fruit bunches based on their maturity using portable four-band sensor system." Computers and Electronics in Agriculture 82: 55-60.

Saeed, O. M. B., A. R. M. Shariff, et al. (2013). "Ripeness Detection of Oil Palm Fresh Fruit Bunches Using 4-Band Sensors." Journal of Advanced Science Letters 19(12): 3468-3472.