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# Optimization of Artificial Neural Networks using Genetic Algorithm for Palm Fruit Ripeness Classification

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**ABSTRACT**

The cultivation of oil palm has become a major contributor to vegetable oil production, playing a crucial role in meeting the global demand for food in the agricultural industry. The efficiency of palm oil extraction heavily relies on accurate fruit ripeness classification, which is traditionally performed manually. Accurate assessments of oil palm fruit maturity levels before processing are crucial for Malaysian producers and exporters. This report outlines a machine-learning approach for sorting palm fruit by utilizing an artificial neural network (ANN) and optimizing its performance via a genetic algorithm (GA). The research specifies input features such as colour, size, texture and output classes that include the phases of unripe, ripe and overripe palm fruits. The Palm Fruit Database was built by acquiring images of palm fruits through the on-site collection and an e-database called ROBOFLOW and then defining their maturity characteristics through image processing techniques. Using MATLAB software, this study applied three different ANN training methods: the Levenberg-Marquardt backpropagation algorithm, the Bayesian regularization backpropagation algorithm and the scaled conjugate gradient backpropagation algorithm, resulting in accuracy scores of 74.96, 86.19 and 74.97% respectively. The Bayesian regulation has the best performance. The initial accuracy of the ANN test was 77%, but after applying GA optimization, the accuracy improved to 87%, a 10% increase. The proposed approach offers a practical solution for improving the efficiency and accuracy of palm fruit classification in the palm oil industry, ultimately leading to better quality control and increased productivity.

## 1. Introduction

Palm oil is a widely used component in various industries and products, including cooking, cleansers, margarine, candles, snack food and processed meals. It is also used as biodiesel. Assessing

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the accuracy of fresh fruit bunch (FFB) maturity levels of oil palm fruits before processing is a major concern for palm oil producers in Malaysia [1,2]. The current method of human evaluation by eye is time-consuming and prone to errors. This has led to the exploration of automated techniques such as image sensors and sensor-based innovations. The most prevalent species of palm oil in Malaysia is *Elaies Guneensis* and its ripeness level is determined by colour, which is affected by lighting conditions [2-4]. The Malaysian Palm Oil Board (MPOB) has identified four ripeness stages for palm oil of FFB: unripe, under-ripe, ripe and overripe. The colour of the fruit is determined by the illumination, making it difficult to manually determine the correct colour due to variations in lighting conditions. Thus, using a neural network algorithm is crucial for determining the ripeness of oil palm fruit [5,6]. Advanced artificial intelligence technologies, such as machine learning or deep learning, are needed to improve the accuracy of FFB maturity detection. For instance, an artificial neural network (ANN) is trained using collected pre-processed images and extracting features from those images. Meanwhile, support vector machine (SVM) and naïve Bayes classifier are used for maturity grading based on the captured colour images [6]. Alfatni *et al.,* [2] proposed a Real-Time oil palm fruit maturity system using ANN; they developed several techniques, such as Gabor, GLCM and BGLAM, to extract fruit image characteristics incorporated to determine the maturity level of FFB. The classifier solution between the SVM, K-nearest neighbor (KNN) and ANN showed that ANN performed well due to the natural noise of the data. Nevertheless, integrating ANN with a potential optimizer like Genetic Algorithm (GA) can further improve the performance.

Features extraction techniques can be applied in this application by determining the characteristics of colour, texture and shape. The fruit variety determines the attributes that are used. Fruit can be classified according to its colour, which offers useful information about its maturity and quality [7]. However, extractions that depend solely on the mean colour will result in inaccurate performance.

A neural network can be optimized using a GA to determine the ripeness of fruits. The genetic algorithm is used to find the optimal combination of hyperparameters for the neural network architecture [8,9]. This approach has been applied in different fields, such as remote sensing and cosmology. In remote sensing, a visible near-infrared hyperspectral imager coupled with a convolutional neural network and genetic algorithm-based feature selection method was used to assess the ripeness of the fruits [10]. In cosmology, genetic algorithms were used to improve the performance of artificial neural networks in modelling large datasets and complex nonlinear functions [10,11]. These applications demonstrate the effectiveness of genetic algorithms to optimize neural networks for ripeness determination and other tasks.

This project proposes a method for constructing a palm fruit segregation model using machine learning, which aims to categorize the stage of maturity of the fresh fruit bunch. A GA-optimized ANN will segregate harvested fruit bunches from palm trees with high efficiency and precision. For this purpose, a fresh palm fruit image processing system will be constructed in the database using the image processing methodology for data extraction of features. MATLAB R2023b software is used to program and extract the features of the signal image input and palm fruit images. The proposed approach provides a practical solution for improving the efficiency and accuracy of palm fruit classification, ultimately leading to better quality control and increased productivity.

### *1.1 Machine Learning*

Machine learning has rapidly advanced in recent years, using statistical methods to train algorithms for classification and prediction [12,13]. The core of a machine learning solution involves collecting data, training a model and applying it to make predictions. Models have been created for image classification, text analysis and speech recognition [14]. An automated oil palm FFB classification system using an ANN based on image classification techniques has been developed to categorize the FFB into maturity categories. However, the system's sensitivity to changing light intensities limits its use in settings where lighting conditions remain inconsistent. Data collection in agricultural and food processing settings requires the use of various sensors, such as colour, spectral, thermal, acoustic, three-dimensional depth and tactile sensors [15]. Hyperspectral cameras have demonstrated the ability to precisely capture an object's reflectance through wavelength measurements, rendering them less vulnerable to a range of environmental factors and enabling the recognition of separate objects.

During image processing, a key component that is widely used in various fields is the pre-processing and image segmentation stage. The main purpose of this stage is to reduce the amount of information in the image, enabling ease of analysis and compression, which significantly benefits image analysis and compression [16-18]. Feature extraction is a low-level application that aims to identify the most relevant characteristics of an image, such as colour, texture, shape and size.

The ability to activate and regulate the classification of images is made possible by machine learning techniques. However, a small number of training samples were used to create deep convolutional neural networks, multi-band deep learning and modular features to identify the remotely detected data from the hyperspectral, hyperparameter, spectroradiometer and spectrometer images [2].

ANN is a vital component for classifiers due to its exceptional computational capabilities, allowing it to generate an output that precisely matches the intended output [18-20]. ANN computational models are often used to produce outputs that closely match the desired target, requiring the use of Mean Square Error (MSE) to train the ANN with multiple cycles of training [20,21]. The performance of an ANN classifier is evaluated based on its specificity and sensitivity, which are measured independently. The ROC curve evaluation is the industry standard for assessing predictive accuracy in model and prediction algorithm evaluation and comparison [2]. Therefore, the improvement of functionality and performance of palm fruit system can be improved by proposed a variety methods and techniques based on the system software. Table 1 shows the use of ANN classification methods that resulted in varying accuracy performance.

**Table 1**
The literature on the use of a variety of classifiers

| Ref | Dataset | Feature extraction technique | Classifier (Accuracy %) |
|---|---|---|---|
| [2] | Oil Palm Fruit Images | Statistical data: Histograms, Gabor Wavelet, GLCM, BLGM, Different sizes of Images | ANN:93% SVM:77% KNN:76% ROC Curve |
| [3] | Oil Palm Fruit Images | LED and Optical Sensor (a light source with 670nm wavelength) | Statistical Data: Mean, Variance, Standard Deviation |
| [7] | Oil palm fruit images | Principle Component Analysis (PCA) | ANN: Confusion matrix, Acc 98.3% |
| [9] | Oil Palm Fruit Spectra | NIR & PCA | GA-ANN: Training 86.3%,Val:84.5% MAE,MSE,RMSE |
| [12] | Oil Palm Fruit Images | Segmentation | ANN Prediction: 0.6934 Validation: 0.7211 |
| [16] | Palm Oil fertile Images | GLCM | Euclidean Method |

| | | | |
|---|---|---|---|
| [22] | Building Type | Heating load of energy efficiency of building: GLAD, GLA, O, OH, RA | GA-ANN :RMSE=1.625, R2=0.980, MAE=0.998<br>PSO-ANN: RMSE=1.932, R2=0.972, MAE=1.027<br>ICA-ANN: RMSE=1.982, R2=0.970, MAE=0.980<br>ABC-ANN: RMSE=1.878, R2=0.973, MAE=0.957 |

### *1.2 Optimization Prediction using Genetic Algorithm*

Optimization is the process of maximizing or minimizing a particular objective function while adhering to functional constraints. Optimization prediction using GA has gained attention due to its population-based approach that uses binary strings to represent variables instead of actual values. The GA is an optimization approach that determines a function's optimal values by applying the biological theory of natural selection. This allows GA to handle discontinuous functions and efficiently search for solutions with high reliability in many areas [2,22-24]. Neural networks have been successfully integrated with GA to enhance their learning and input selection capabilities, making GA a prime example of evolutionary computing. It involves concepts of crossover, natural selection, genetics and mutation. The ANN is trained using the error function as the goal function and weights are modified to reduce error [24]. Chromosomes hold various parameters and the inversion operator may be used in homogeneous loci. The initial population is evaluated based on how well the GA works [25]. While GA slightly outperformed the other methods in terms of optimality, it was observed to be time inefficient compared to random search and Bayesian optimization [26]. The advancements have great potential for improving agricultural processes, allowing for more accurate and efficient analysis and classification of agricultural products.

## 2. Methodology

This section shows the optimization approach of this project work with the agreed specification for classifying agricultural products using an ANN and GA. Figure 1 shows the methodology process that includes data image acquisition and image preprocessing, feature extraction, an ANN and optimization using a GA.

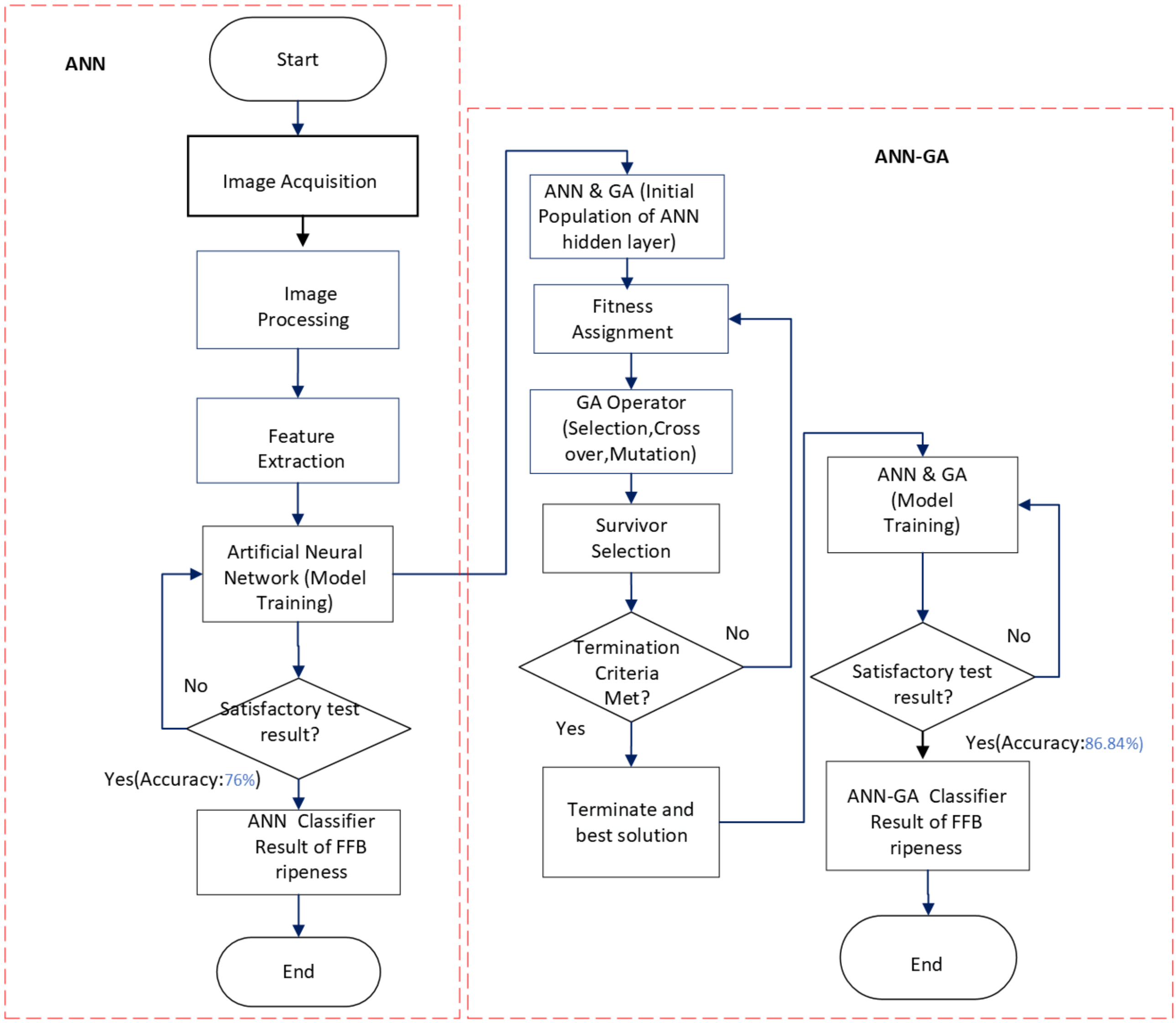



**Fig. 1.** The methodology process of the project work

### *2.1 Image Acquisition*

Images of the palm oil FFBs dataset were obtained from two types of collection, namely the on-site collection at Felda Rasau Kerteh, Terengganu and the license-website collection by the ROBOFLOW platform, the largest resource offering complete datasets with a promising end goal of providing a good data set with high degree of accuracy.

The palm fruit data collection is based on the image presented in Figure 2, which shows the class of fruit ripeness based on colour inspection and shape.

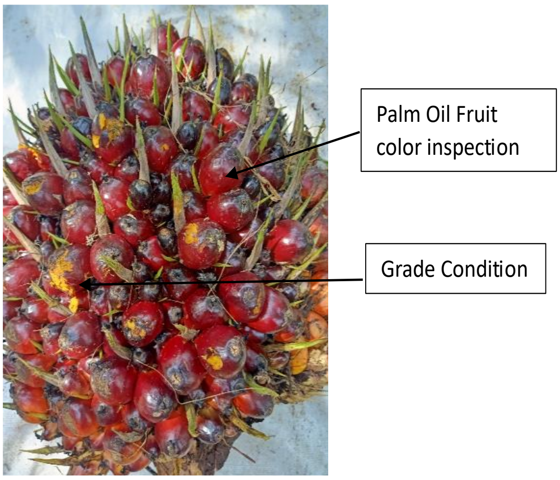



**Fig. 2.** Palm fruit bunch sample data collection

Table 2 shows a sample of palm fruit list criteria from different classes, such as the fruit colour, shape and skin shine.

**Table 2**
Overall palm fruit bunch collection criteria for each category

| Overripe criteria | Ripe criteria | Unripe criteria |
|---|---|---|
| Not shiny | Clean and shiny | Very shiny |
| Reddish | Reddish and orange colour | Darkish colour |
| Not well-shaped/broken skin | Well shapely | Small shape |

There are certain characteristics for identifying whether a fruit is overripe, ripe or unripe. Overripe fruits usually have a dull appearance, reddish colour and misshapen or broken skin. On the other hand, ripe fruits are clean and shiny, with a mix of reddish-orange colour and a well-formed shape. Unripe fruits, on the other hand, usually have very shiny, darkish skin and are small in shape. A total of 300 images of FFBs were collected to determine the respective category of the overall FFBs class, namely ripe, unripe and overripe. Data augmentation is employed to increase data volumes during analysis by adding altered versions of existing data or synthesizing new data. It acts as a regularizer to prevent overfitting in machine learning training.

*2.2 Image Processing*

The image processing stage involved various methods, including noise reduction, conversion of RGB to grayscale images and extracting images using feature extraction techniques. Noise reduction techniques were employed to reduce image graininess. Chroma and brightness levels of the colour pixels were adjusted accordingly. The next step involved resizing the images to maintain the original aspect ratio, which required identifying the larger dimension in the image. This dimension should be adjusted to match the maximum dimension of the desired output. The RGB images are then converted to grayscale images, represented only by their intensity level. The intensity level ranges from 0 to 255 pixels in a variety of grey tones. The grayscale image of palm oil fruits is converted to a binary colour space, meaning each pixel is represented by a single bit (0 or 1). The distinct variation in distance is a crucial feature of a binary image that indicates the position of the space within the pixel closest to each of the already existing pixels. Otsu's method is a widely used technique for automatically determining the global threshold value of an input grayscale image for image segmentation.

### 2.3 Feature Extraction

The process of feature extraction involves identifying and extracting relevant information from an image. This information can be used for object detection, recognition, categorization and tracking. Three feature extraction methods commonly used are Speeded-Up Robust Features (SURF), Histogram (HOG) and Local Binary Pattern (LBP). SURF is used to detect and extract points of interest in an image. It has the ability to withstand variations in rotation, scale and lighting, making it useful for a variety of applications. This technique computes a set of descriptors for each interest point once it is detected. The HOG provides a way to represent the distribution of pixel intensities in an image. The colour histogram features are computed by dividing the colour space into bins and counting the number of pixels that fall into each bin. LBP is a method for extracting features by encoding the local texture information of an image. It computes a binary code for each pixel by comparing its intensity value with the intensity values of its neighbouring pixels. SURF, HOG, LBP and histogram features are retrieved from the image processing simulation. In order to develop a model capable of separating palm oil FFBs into several groups according to their ripeness, the machine learning algorithm can be fed with the corresponding characteristics.

### 2.4 An Artificial Neural Network

The ANN classifier was developed when the image processing process was completed. ANN is made up of neurons coupled by weights and biases. Figure 3 shows an ANN model architecture. The next stage after establishing the ANN's structure is to train the network. The module was generated by the neural pattern recognition app and consists of a set of functions and parameters that define how the network operates.

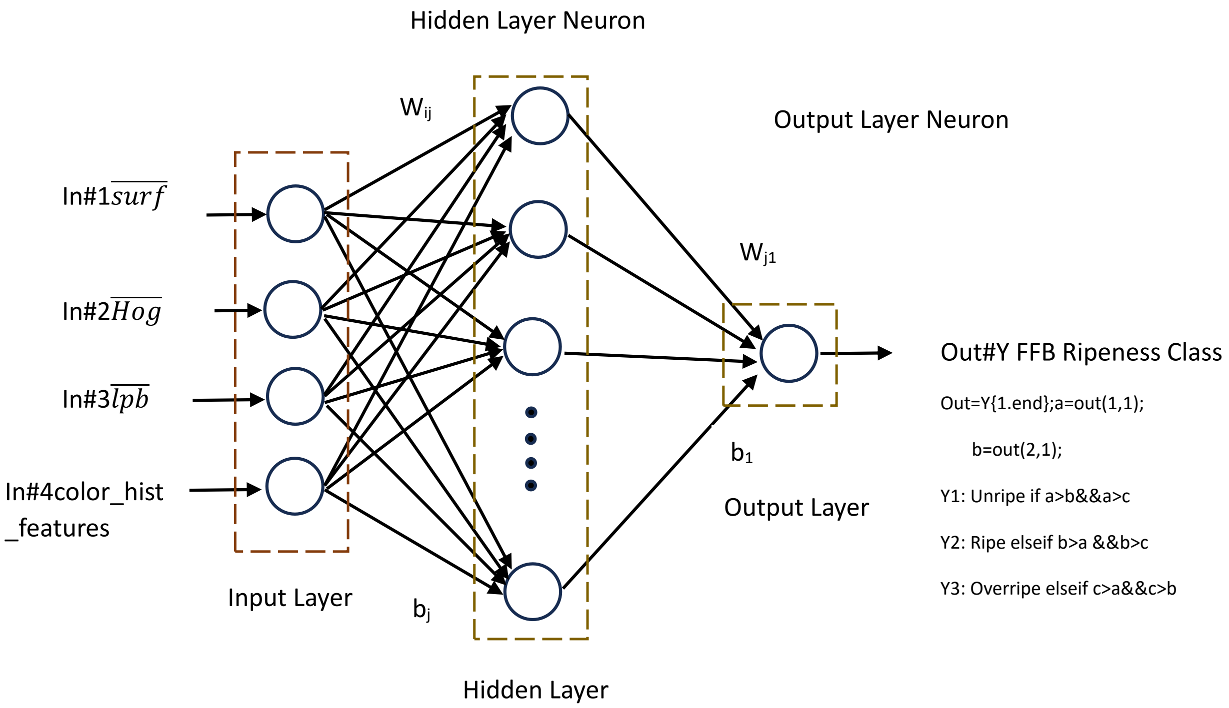



**Fig. 3.** An artificial neural network architecture

The ANN was trained using three different backpropagation algorithms: Levenberg-Marquardt (trainlm), Bayesian regularization (trainbr) and scaled conjugate gradient (trainscg); each for a given set of normalized input data (x) and target data (t). The input data was divided into three sets for training, validation and testing using the divider and function, with a training ratio of 80%, a validation ratio of 10% and a testing ratio of 10%. Thus, to prevent numerical overflow, the data derived from the experimental values were normalized between 0 and 1. The normalization process was carried out using the following Eq. (1):

$$y_i = (x_i - x_{\min})/(x_{\max} - x_{\min}) \tag{1}$$

Where, xmax and xmin represent the maximum and minimum values of xi, respectively and yi is the normalized value of $x_i$.

*2.5 Classifier Evaluation Performance*

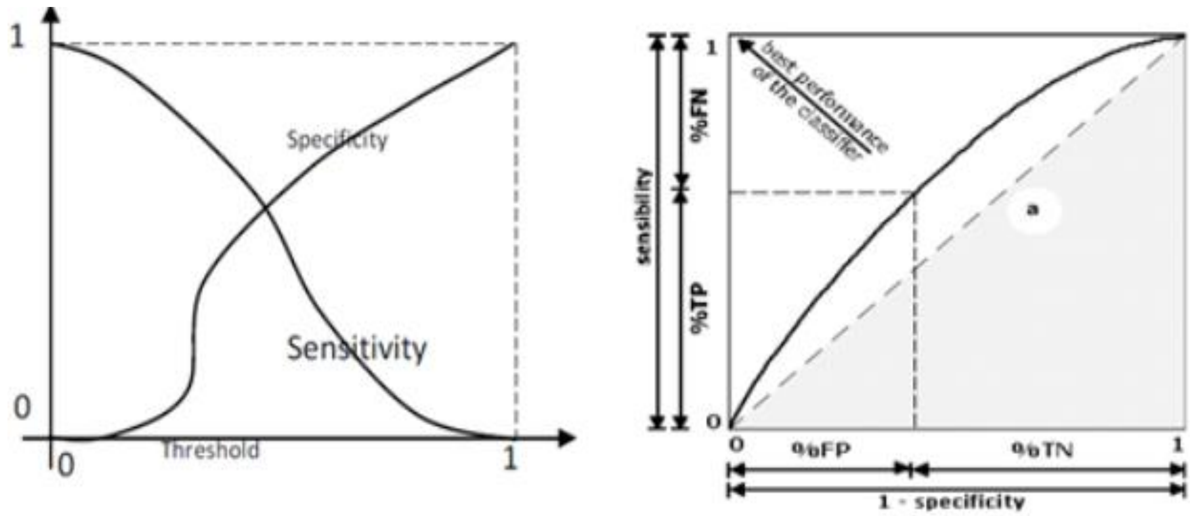
The MSE is a performance metric in neural networks calculated by taking the average of the squared differences between the predicted values and the actual values. The formula for MSE was referred to the Eq. (2):

$$MSE = (1/n) * \Sigma(y_i - \hat{y}_i)^2 \tag{2}$$

Where,
n is the number of data points
$y_i$ is the actual value of the i-th data point
$\hat{y}_i$ is the predicted value of the i-th data point

A systematic evaluation of the sensitivity and specificity of the decision is provided by ROC analysis. The classifier's sensitivity is its ability to determine a positive pattern among positive patterns. The classifier's specificity is its capacity to identify negative patterns amongst negative patterns. Sensitivity is the classifier's ability to determine a positive pattern among genuinely positive patterns. The classifier's specificity is its capacity to distinguish between harmful patterns and those that are not.

Figure 4(a) shows that the optimal classifier is located at point (0,1), correctly classifying all positive and negative cases. Here, the true positive rate is all (1) and the false positive rate is zero (0). Points (0,0) and (1,1) correspond to classifiers that match all positive examples, respectively and show that the classifier anticipated all cases to be negative. Point (1,0) indicates that the classifier is unable to apply the proper classification in all situations, as shown in Figure 4(b).




(a) (b)

**Fig. 4.** (a) Graphs of sensibility versus threshold, specificity versus threshold and (b) ROC curve with a hypothetical example [2]

The accuracy is computationally calculated as referred to the Eq. (3), (4) and (5) below:

$$Accuracy = \frac{TP+TN}{n} \tag{3}$$

$$The\ True\ Positive\ Rate\ (TPR) = Sensitivity = \frac{\sum TP}{\sum TP + \sum FN} \tag{4}$$

$$The\ False\ Positive\ Rate\ (FPR) = Specificity = \frac{\sum FP}{\sum FP + \sum TN} \tag{5}$$

The number of maturities successfully categorized is the genuine TP positives. Actual drawbacks, the number of ripeness that are incorrectly classified is referred to as TN. The number of ripeness labelled as non-ripeness and false negatives is known as false positives or FP. The number of non-ripeness categorized as maturities is referred to as FN. In summary, evaluating the oil palm FFB ripeness classification system classifier's performance, in general, involves the assessment of sensitivity and specificity, as performance outcomes are based on the ROC curve. The classifier classifies fruit as unripe, ripe or overripe based on the output values of the neural network performed well.

### *2.6 Optimization using Genetic Algorithm*

A GA is a type of optimization algorithm inspired by the principles of natural selection, whereas genetics was used to optimize the value of a function to represent one branch of evolutionary computation. In ANN, network parameters are represented as matrices since this facilitates computations. In GA, chromosomes are ID vectors; thus, the weight matrices were transformed into 1D vectors. A multiplication matrix is used for ANN and matrix-to-vector conversions are necessary for GA. Consequently, matrices are utilized while working with ANN and vectors are utilized when dealing with GA. This necessitates the matrix – vector conversion returns a fitness value for each solution. Fitness values were calculated to determine the superiority of solutions and optimal solutions were returned to parents during the parents' selection stage. This ensures efficient computations and accurate results. GA is considered an effective and comprehensive search algorithm in this sense.

The following are some potential specifications for the executable GA, as shown in Figure 5.

i. Initialization: Population origination is a population of individuals in the population represent a set of neural network parameter which is weight and bias encoding in form of matrices and vectors. Algorithm : *Population size = 100;*
ii. Fitness Evaluation: The conversion matrices to vector returns a fitness value for each individual solution. This individual solution is used to configure the neural network, which is then trained on a dataset of palm fruits. The performance of the ANN on a validation set is used as the fitness function. It could be measured by AUC graph.
iii. Selection: Individuals with higher fitness are more likely to be selected for reproduction. Selection method include roulette wheel selection, tournament selection or rank-based selection.
iv. Crossover: Using the probability method of crossover by a selected individuals are paired to create new offspring. Algorithm: CrossoverFcn,*{@crossoverintermediate, 0.5}.*
v. Mutation: Potential variant selected to form new offspring by altering some of their genes (i.e., parameter). A small probability is set for mutation. Algorithm: *MutationFcn, {@mutationadaptfeasible, 0.05}.*
vi. Stop condition: Check the state to terminate the algorithm. This could be a set number of generation. Algorithm : *Generations = 50*
vii. Select the result: If stopping criteria are met, the algorithm ends and the best solution is generated in a new population. If criteria are not met, society will be continually created by repeating three steps: selection, crossover and mutation. Algorithm resulted the final output is a neural network optimized by the GA, ideally provide an accurate and efficient palm fruit segregation.

Stopping conditions:

i. The number of converging genes is controlled by the chromosome structure; if the number of genes reach a certain point or exceeds it, the algorithm terminates.
ii. Examine how the algorithm changes with each generation based on the unique significance of each chromosome. The algorithm terminates if the difference is smaller than a constant.

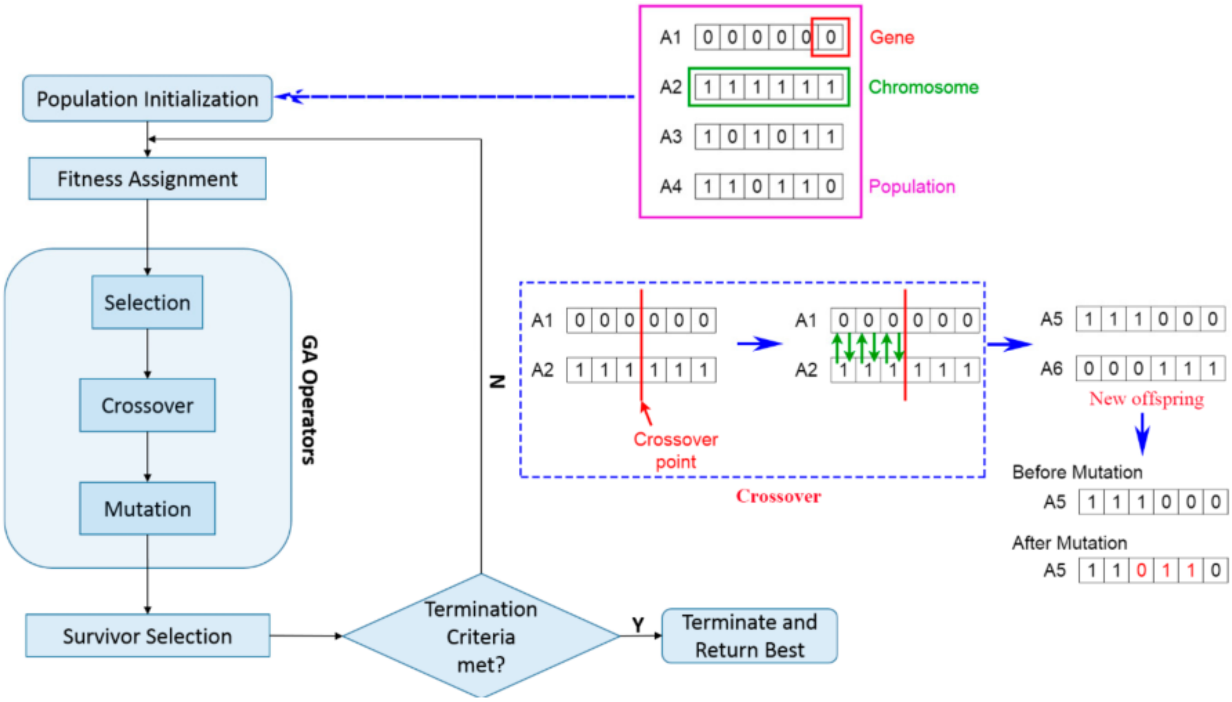



**Fig. 5.** Methodology of a genetic algorithm [22]

The Neural Pattern Recognition app produces a script that incorporates GA optimization. The goal of the GA optimization is to identify the ideal quantity of hidden neurons of the ANN. In order to achieve this goal, the fitness definition and the GA parameters are established, including the number of variables to be optimized, which is the number of hidden neurons ranging from 1 to 30. As well, the GA options of population size of 100, 50 generations and crossover and mutation feasibility are 0.05. While chromosomes in GA are 1D vectors, convert the weight matrices to 1D vectors as well. Finally, the optimized number of neurons is used to train the ANN and then evaluated using various performance metrics, such as accuracy, sensitivity and specificity.

## 3. Results and Discussion

The outcomes of the image processing process, feature extraction and ANN model training and testing, as well as the system classification results, were achieved using MATLAB simulation. A result comparison of the ANN model and the GA optimized ANN module's performance is presented.

### *3.1 Image Acquisition and Image Processing*

In pre-process images, a collection of images of palm fruit in different classes, namely ripe, unripe and overripe fruit, was generated. Pre-process image was done to improve the clarity of the image, eliminate noise and solitary the palm fruit from the background.

Figure 6 shows a series of pre-processing image processes. This was accomplished by resizing images to 128x128 pixels, normalizing, converting RGB images to grayscale using a Gaussian filter and binarization global thresholding by Otsu’s method subjected to applying morphological processes to the images.

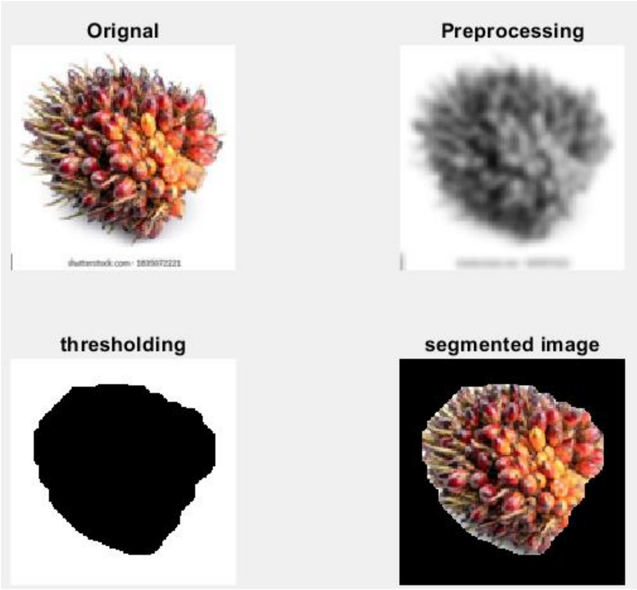


**Fig. 6.** A series of pre-processing images step process

### *3.2 Feature Extraction and Normalization Data*

The processing process results are then extracted to feature characteristics using surf, HOG and LBP. The'surf_features', 'hog_features', 'lbp_features' and 'hist_features' variables held the extracted features in one single table, whereas 'class_labels_all' received the class labels. The extracted features were normalized and combined with their corresponding class. The extraction data is then used for training and evaluating the ANN model.

### *3.3 An ANN Module Training and Test Evaluation*

The ANN module was developed using the Neural Pattern Recognition app with 15 hidden layers, trained on a dataset containing four features and three output classes. The ANN was trained using three different training modes: the Levenberg-Marquardt back-propagation, the Bayesian regularization backpropagation and the scaled conjugate gradient backpropagation, while the three different training modes used random data division and achieved accuracy ranging from 74.96 to 86.19%, with convergence requiring between 24 and 1000 epochs.

Table 3 shows the performance score of ANN using three different training modes. The first mode shows the Levenberg-Marquardt back-propagation algorithm achieved a performance score of 0.2343, the trainPerformance scored 0.2333, the valPerformance scored 0.2261 and the testPerformance scored 0.2504. Meanwhile, the accuracy scored 74.96% at 24 epochs. The second mode, showing the Bayesian regularization backpropagation achieved a performance score of 0.2161, the trainPerformance scored 0.2139, the valPerformance scored NaN and the testPerformance scored 0.2358. Meanwhile, the accuracy scored 86.19% at 1000 epochs. The third mode shows the scaled conjugate gradient backpropagation algorithm achieved a performance score of 0.2475, the trainPerformance scored 0.2502, the valPerformance scored 0.2355 and the testPerformance scored 0.2381. Meanwhile, the accuracy scored 74.97% at the epoch.

**Table 3**
The three different training modes for training ANN

| Performance function | ANN training mode | | |
|---|---|---|---|
| | Levenberg-Marquardt back-propagation | Bayesian regularization backpropagation | Bayesian regularization backpropagation |
| Performance | 0.234 | 0.2161 | 0.2475 |
| trainPerformance | 0.233 | 0.2139 | 0.2502 |
| valPerformance | 0.226 | NaN | 0.2355 |
| testPerformance | 0.250 | 0.2358 | 0.2381 |
| Accuracy (%) | 74.96 | 86.19 | 74.97 |

### *3.4 The GA Module Training and Test Evaluation*

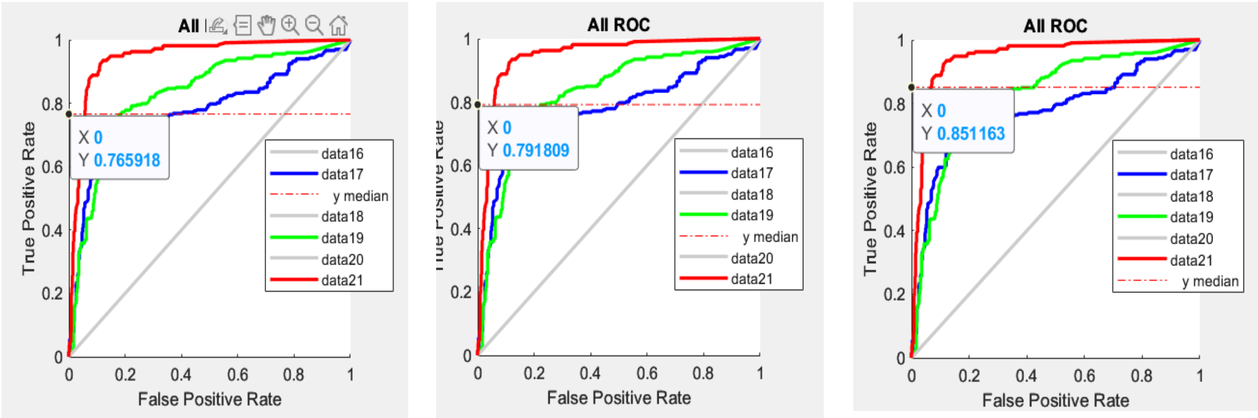
The accuracy of the ANN model and ANN-GA is calculated by comparing the FFB ripeness predicted classes with the actual classes in the target data. The Neural Pattern Recognition app produces a script that incorporates GA optimization. The goal of the GA optimization is to identify the ideal quantity of hidden neurons for the ANN. To achieve this, the GA parameters are established, including the number of variables to be optimized, which is the number of hidden neurons ranging from 1 to 30, as well as GA options like a population size of 50 and 10 generations. The fitness of each solution is then evaluated using a fitness function, which is defined as the MSE between the target data and the output of the ANN model with the given number of hidden neurons.

The accuracy of the ANN model is calculated by comparing the predicted classes with the actual classes in the target data. Table 4 shows that the accuracy increased from 76 to 86.84% after applying the GA optimization. The performance of the ANN model also improved, as indicated by the decrease in the mean squared error from 0.24535 to 0.2150. The ROC curves for each class also indicate better performance after GA optimization was applied.

**Table 4**
The FFB ripeness predicted the class result of the ANN model and ANN-GA

| | | ANN Model | ANN-GA |
|---|---|---|---|
| Feature Extraction characteristic ($\overline{surf}, \overline{Hog}, \overline{lpb}$ colour_hist_features) | Accuracy (%) | 76 | 86.84 |
| | MSE (Value) | 0.24535 | 0.2150 |

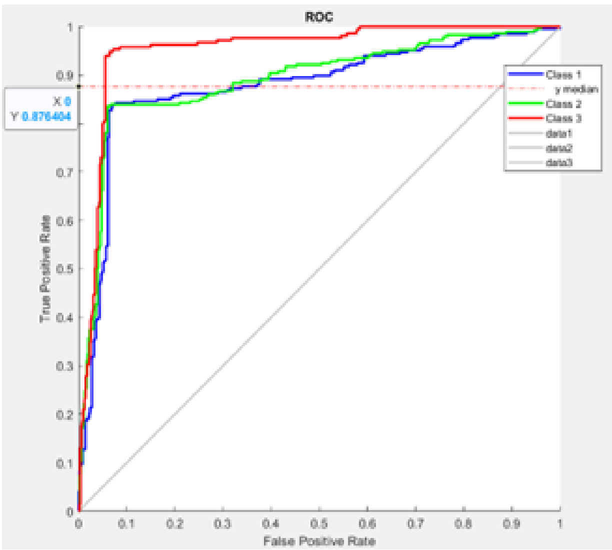
Figure 7 shows the graph performance of ANN classes. An enhancement in the performance of classes 1, 2 and 3 was noted, as demonstrated by the ROC curves. It can be observed that the ROC curve medians for each class increased from their original values of 0.7659, 0.7918 and 0.8512, indicating better performance.



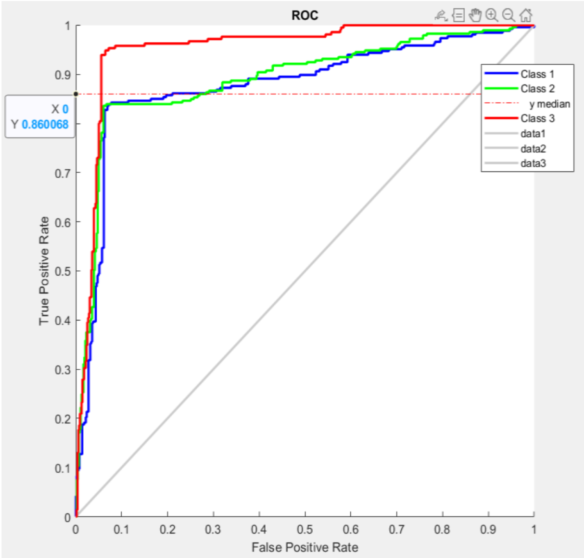

(a) (b) (c)

**Fig. 7.** The ROC graph performance of classes before GA (a) 12 class 1 ROC before GA, (b) class 2 ROC before GA and (c) class 3 ROC before GA

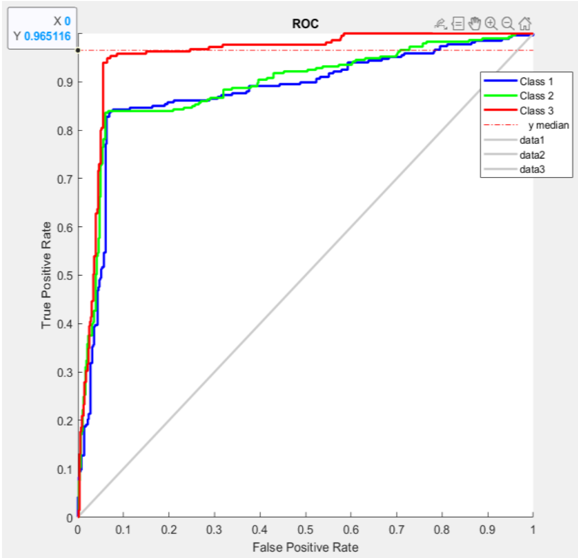
Figure 8 shows the ROC graph performance among classes after ANN-GA optimization. Specifically, the new median values for the ROC curves are 0.87, 0.86 and 0.95. The evaluation result was summarized: the GA optimization code improves the accuracy and performance of the ANN model by finding the optimal number of hidden neurons. The initial ANN test had an accuracy of 76%; after applying the GA optimization, the accuracy increased to 87%, which is an improvement of 10%. The GA algorithm searches the space of possible solutions efficiently and the fitness function guides the optimization towards better solutions. Thus, the resulting ANN model can be used to classify new data with higher accuracy and better performance**.**




(a) 12 class 1 ROC after ANN-GA




(b) class 2 ROC after ANN-GA




(c) class 3 ROC after ANN-GA

**Fig. 8.** The ROC graph performance of classes after ANN-GA (a) 12 class 1 ROC after ANN-GA, (b) class 2 ROC after ANN-GA and (c) class 3 ROC after ANN-GA

## 4. Conclusions

This paper successfully presented the development of an approach to the optimization of Artificial Neural Networks using a Genetic Algorithm for Palm Fruit Ripeness classification, compared to the current method of manual evaluation by human eye sense. The FFB images database was collected, defining the feature characteristics and FFB maturity classification by incorporating several processes of image processing techniques, ANN and GA. The dataset of palm fruit images with different ripeness stages was pre-processed images using ANN and GA initialization to ensure uniformity and enhance relevant features. This approach allows for automated exploration of the solution space and potentially leads to better results compared to traditional manual tuning methods. The simulation result using MATLAB reported that the adoption of ANN hidden layer in the initial population of GA can achieve optimization performance, which led to a 10% increase in accuracy compared to the ANN original model. The result scored is 77% for ANN and 87% for ANN-GA. Three different ANN training methods show the variety of technique approaches, including the Levenberg-Marquardt backpropagation algorithm, Bayesian regularization backpropagation algorithm and scaled conjugate gradient backpropagation algorithm, which resulted in an accuracy score of 74.96, 86.19 and 74.97%, respectively. A comparison of the three techniques shows a better performance of Bayesian regulation.

Overall, the ROC was used to evaluate and estimate the accuracy of the classifier performance. The ROC curve result shows that the sensitivity and specificity were able to recognize the positive pattern and negative pattern of the FFF ripeness class into unripe, ripe and overripe. However, the proposed ANN-GA with various approaches for feature extraction technique, ANN-GA parameter, can be further investigated. Incorporating the model development process can be further improved, including image data collection, ANN hidden layer upgrade and GA parameters. The development of an ANN and ANN-GA model for FFB segregation led to a 10% increase in accuracy compared to the original model. The performance of the GA-optimized ANN model was evaluated and compared with the original model. Various visualizations were created to gain insights into the behaviour of the model. Findings suggest that the GA has the potential to optimize the architecture of artificial neural networks, which could prove useful in real-world engineering applications, multi-objective optimization problems and optimization problems with constraints.

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