Application of Particle Swarm Optimization Algorithm for Optimizing ANN Model in Recognizing Ripeness of Citrus

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Abstract. This paper shows findings of the application of Particle Swarm Optimization (PSO) algorithm in optimizing an Artificial Neural Network that could categorize between ripeness and unripeness stage of citrus suhuensis. The algorithm would adjust the network connections weights and adapt its values during training for best results at the output. Initially, citrus suhuensis fruit’s skin is measured using optically non-destructive method via spectrometer. The spectrometer would transmit VIS (visible spectrum) photonic light radiation to the surface (skin of citrus) of the sample. The reflected light from the sample’s surface would be received and measured by the same spectrometer in terms of reflectance percentage based on VIS range. These measured data are used to train and test the best optimized ANN model. The accuracy is based on receiver operating characteristic (ROC) performance. The result outcomes from this investigation have shown that the achieved accuracy for the optimized is 70.5% with a sensitivity and specificity of 60.1% and 80.0% respectively.
1. Introduction

In Malaysia, the agriculture sector is growing and increasing demand among consumers. One of them is “Limau Madu” or scientific name is citrus suhuiensis. It belongs of the rutaceace family and one of the local fruit that has high potential for development and demand. It has a sweet taste, content of juice is high, good fruit size and have less fiber and bagasse [1]. Nowadays, fruit industry is important in term of economic and social. There are a variety of local fruits available either seasonal or non-seasonal such as watermelon, citrus, pineapple, banana and etc. Based on new technology and research done, fruits can be cloned so that the production of fruit can be increased and quality of fruit can be control [2]. However, the research on how to identify maturity of fruit are still ongoing progressively and widely available. Traditional way of identifying ripeness of fruit can be determined by an expert person that has experience and skill. Recently, many researches were done in recognizing ripeness of citrus by using PSO algorithm and Artificial Neural Network [4-6].

The ability to classify the quality either ripeness or unripeness will benefit for both farmers and consumers. Besides that, it will help the farmer to grade the fruit in different size and price. To commercialize a local fruit such as citrus suhuiensishort., many aspects must be considered in order to increase its productivity. It was reported that the process of maturity stage is within the 8-10 month, where the skin will become oily glands and soft [3]. However from observations, the skin color is the same whether it is within growth stage or maturity stage.

The objective of this work is to recognize ripeness and unripeness of Citrus Suhuensis using Particle Swarm Optimization algorithm by adjusted their connections weights with different hidden layer size. The new weights are predicted by PSO algorithm during training of an Artificial Neural Network (ANN). A reflectance spectrometer is used as a tool for nondestructive determination of the citrus’s ripeness condition. The percentage reflectance from the spectrometer is based on wavelength of green, orange and yellow color.

2. Instrumentation

2.1. Visible Spectrum (VIS)

By viewing a substance through a spectrometer, one can distinguish the exact mixture of color, which corresponds to specific wavelengths of light. VIS has been chosen as the light reflectance, where it consists of a spectrum of wavelengths which range from of 400 to 780nm as shown in Figure 1 [7]. This visual spectrum is used in order to see through the sample experiments and it can be related to the electrical instrument (spectrometer) being used. These wavelengths are used by spectrometer in order to collect data in term of percentage and reflected light that received back to the spectrometer.

![Visible Spectrum](image)

Figure 1: Optical properties of VIS
2.2. Spectrometer

A spectrometer is a device that splits light into various colors. The waves of visible light can see as color of rainbow, where each color has different wavelengths. In this project, spectrometer is used to measure the amount of light. Spectrometer is a device that transmit light beam from a source and read from intensity of light reached by receiver or detector as shown in Figure 2. It provides optical measurements in the ultra-violet (UV)/visible spectrum (VIS) and Near Infra Red (NIR) spectral range. The spectrometer, MCS600 is suitable for measurements in the UV range, versatile tasks and a very high degree of flexibility can be fulfilled [8, 9, 10]. The spectrometer is attached with the head labelled as OFK30. This spectrometer can cover a spectra range between 190 to 2200 nm [11]. The result obtained from the light reflectance head is interpreted by Aspect Plus software.

![Figure 2: Spectromter](image)

2.3. Particle Swarm Optimization

Particle swarm optimization (PSO) is a new method of optimization developed in 1995 by Kennedy and Eberhart [12]. The idea of PSO was inspired by social behavior of bird flocking, fish schooling and as well as swarming theory. The concept of PSO is that, each particle will searched space to find the best solution (fitness) which called pbest. Every single particle has their own pbest value even though it can’t achieve the global value called gbest. Each particle has the ability to memorize and track the current best particle (pbest) in a swarm [13]. In the proposed method, the solution vector represents all the ANN’s weight values. In order to minimize the problem of ANN training to PSO algorithm, the weights and biases of a network are predicted by PSO algorithm.

Generally, PSO used to replace the architecture of the Artificial Neural Network (ANN) because the train in ANN takes a lot of time and it only based on trial and error [14]. The basic concept of PSO technique lies in accelerating each particle towards its pbest and the gbest locations at each time step. Acceleration has random weights for both its pbest and the gbest locations [15]. These are different between each other and greatly depend on hidden layer size, input, bias and output. Two factors characterize a particle status on the search space: its position and velocity. The most popular formulations of how particle adjusts its velocity and position are shown in equations (1) and (2).

\[
V_i(t+1)(d) = Wv_i(t)(d)+C_1 r_1(P_b_i(t)-x_i(t))+C_2 r_2(G_b_i(t)-x_i(t)) \tag{1}
\]

\[
X_i(t+1)(d) = x_i(t)(d)+v_i(t+1)(d) \tag{2}
\]
Where, d is the indexes of dimension in the search space, represents the inertia weight, and are regarded as cognitive and social parameters for algorithm respectively, and are two random numbers is the personal best position recorded by particle I, while is the global best positions obtain by any particle in the population [16].

3. Methodology

3.1 Data Collection.

Data were taken from previous researcher. The samples of citrus were classified first by an expert person for either ripeness or unripeness. 200 samples of citrus were used for this project where 100 samples for each ripeness and unripeness respectively. Each sample’s skin was divided into 6 portions, and data reflectance by spectrometer was measured for each of this portion. Thus, the total data for ripeness and unripeness is 1200 and 600 respectively. Table 1 shows an example of 10 samples of the required data being measured.

Table 1: Sample of Data

| No. | Wavelength (nm) | Reflectance (%) | Ripe | Unripe |
|-----|----------------|-----------------|------|-------|
| 1   | 509.144        | 3.57143         | 6.47149 |
| 2   | 512.514        | 4.35931         | 8.32117 |
| 3   | 515.884        | 5.93434         | 8.40336 |
| 4   | 519.255        | 7.07317         | 15.0769 |
| 5   | 569.819        | 15.8774         | 14.1892 |
| 6   | 573.190        | 14.8501         | 13.8085 |
| 7   | 576.561        | 13.9893         | 13.0147 |
| 8   | 590.043        | 11.4418         | 11.5526 |
| 9   | 593.414        | 10.6809         | 11.4328 |
| 10  | 596.784        | 10.5017         | 11.0696 |
|     | OUTPUT         | 1               | 0     |

Table 2 shows the proposed training and testing data set applied in this experiment where the classification output is set as a ‘0’ for unripeness and ‘1’ for ripeness respectively. These data were used to design and train for optimizing 6 ANN model connections weights using PSO algorithm with various hidden layer size. All these models were then validated with the testing set. As depicted in the table, the ratio between training and testing data sets are 400:400 and 100:100 respectively.

Table 2: Sample of Data of Proposed Set

| Classes   | Training | Testing | Output |
|-----------|----------|---------|--------|
| Ripeness  | 400      | 100     | 1      |
| Unripeness| 400      | 100     | 0      |
3.2 Artificial Neural Network

The main goal of artificial neural network modeling is to obtain the weights and minimize the error. The weights of NN training can adjust by default or another algorithm. ANNs are a problem-solving tool that has become an alternative modeling method to some physical and nonphysical systems with scientific or mathematical basis [14]. It nearly attitude of the process of human learning and this intelligent are train like human thinking. Just as human brains can be trained to master some tasks through experiential knowledge and training, ANNs can be trained to recognize patterns and perform optimization through a training process.

The architecture of neural network and PSO are shown in Figure 3. PSO were predicted for each weight and the values were used to train into ANN. For every single number of neuron in the hidden layer, it provides various connections and thus would affect the parameter called as dimension. These dimensions were use as parameter to implement into PSO technique. Therefore, these parameters need to be adjusted for optimization. The total connections (or parameters) plus the necessary bias connections can be computed as below [17].

\[
\text{No. of connection } s = (\text{input } \times \text{hidden}) + \text{bias}^{\text{hidden}} + (\text{hidden } \times \text{output}) + \text{bias}^{\text{output}}
\]  

(3)

Based on data training set described in Table 2, the best optimized model is with respect to hidden layer size. These 6 designed models were later being validated using the testing data set. Classification accuracy will be explained in the next section.

3.3 Model’s Accuracy

The model’s accuracy could be described in terms of confusion matrix. From the confusion matrix, the best accuracy, sensitivity and specificity could be computed. Accuracy is calculated based on value of true positive, true negative, false positive and true negative. Besides that, the threshold value also influence the percentage accuracy, and it could be observed on the Receiver Operating Curve (ROC) plot. Optimization of the trained models was decided using a confusion matrix [18]. Confusion matrix is a matrix for a two-class classifier, contains information about actual and predicted classifications done by a classification system [19]. Table 3 describes the confusion matrix for a two cases classifier.
Table 3: Confusion Matrix

| Actual/Target | True (-ve) | True (+ve) |
|---------------|------------|------------|
| Predicted Class | Predict (-ve) | TN | FN | Predict (+ve) | FP | TP |

The entries in the confusion matrix have the following meaning is defined as:
- Predicted (+ ve) - the correct predictions
- Predicted (- ne) - the incorrect predictions
- Actual (+ ve) - the actual correct number
- Actual (- ne) - the actual incorrect number
- TN (true negative) - the number of correct predictions that an instance is negative
- TP (true positive) – the number of correct predictions that an instance is positive
- FP (false positive) - the number of incorrect predictions that an instance is positive
- FN (false negative) - the number of incorrect predictions that an instance is negative

Sensitivity and specificity are commonly used terms that describe the accuracy of a test. Sensitivity is a measure of the ratio or percentage of true positive (TP) and a positive actual test (A+). It is also known as true positive rate (TPR) which is the proportion of positive cases that were correctly identified, as calculated using the equation:

$$TPR = \frac{TP}{TP + FN}$$  \hspace{1cm} (4)

Specificity is a measure of the ratio or percentage of true negative (TN) and a negative diagnosis test (A-). It is also called as true negative rate (TNR) which is the proportion of negative cases that were correctly identified, as calculated using the equation:

$$TNR = \frac{TN}{TN + FP}$$ \hspace{1cm} (5)

Percentage accuracy is calculated from the ratio of TPR plus TNR with the total of all samples. The equation is shown below:

$$\text{Accuracy} \% = \frac{TP + TN}{TP + FN + TN + FP} \times 100$$ \hspace{1cm} (6)

At the final stage of this investigation, the performances of all the trained ANN models were analyzed by observing the most appropriate threshold level which would be decided by analyzing the minimum Euclidean Distance (ED) values from the receiver operating characteristic (ROC) plot [20].
4. Result and Discussion

4.1 ANN Model Designing

The 6 models were designed of ANN which focuses on 5, 10, 15, 20, 25 and 30 neurons located in the hidden layer size of the network architecture. The total samples of data used were 1000 for both ripeness and unripeness citrus. These data were divided into two parts where 800 is for training set and 200 is for testing set. From the experiment done, the best optimized model has 20 neurons located in the hidden layer. This optimized model produced an accuracy of 70.5% as shown in Table 4. The best model would have the highest accuracy. From the table, this model has the highest accuracy and the identified best threshold is computed as 0.7 as shown in Figure 4.

| Neurons | Threshold | Accuracy(%) |
|---------|-----------|-------------|
| 5       | 0.5       | 60.0        |
| 10      | 0.5       | 50.0        |
| 15      | 0.5       | 64.5        |
| 20      | 0.7       | 70.5        |
| 25      | 0.3       | 60.5        |
| 30      | 0.1       | 64.0        |

Figure 4: Accuracy ANN Model by using PSO of citrus.

Every hidden layer size has different accuracy when tested with the testing data set. The accuracy of each model was based on value of threshold from 0 to 1 from the ROC plot and confusion matrix. Table 5 shown the confusion matrix after the experimental work and it contains values for TN, TP, FN and FP.
Table 5: Confusion Matrix After Experiment

| Actual/Target | True (-ve) | True (+ve) |
|---------------|------------|------------|
| Predicted Class | Predict (-ve) | 80 | 39 |
|               | Predict (+ve) | 20 | 61 |

Besides that, the results also show in term of sensitivity and specificity. The values for sensitivity (TPR ripeness), specificity (FPR unripeness) and accuracy, could be calculated in manually. Based on equation (4), (5) and (6) the value of accuracy, TPR for ripeness and TNR for unripeness are calculated as below. Analytically, this model could recognize and classify better if tested with unripeness citrus rather than freshness where the specificity scores 80%. However, its capability is reduced to 61% when recognizing ripeness citrus.

\[
TPR = \frac{61}{61 + 39} \times 100 = 61.0\%
\]

\[
TNR = \frac{80}{80 + 20} \times 100 = 80.0\%
\]

\[
\text{Accuracy (\%)} = \frac{80 + 61}{80 + 39 + 20 + 61} \times 100 = 70.5\%
\]

Receiver Operating Characteristics (ROC) usually is used to show the true positive rate (TPR) versus the false positive rate (FPR) across multiple thresholds. It is used to verify the optimal threshold and to maximize classification accuracy and minimize classification errors [19]. To get the best accuracy, it must consider the best value of threshold that is closer in terms of Euclidean distance to the ideal point (0,1).

![Figure 5: ROC of hidden layer size with 20 neurons](image)

Figure 5 shows the ROC plot for hidden layer size with 20 neurons. From the figure, the best threshold is 0.7 where at that point the value for FPR is low at 0.2 while the TPR is the highest at 0.61. In addition, the curve also shows closeness, leaning towards to the y-axis and x-axis.
5. Conclusion

This paper presents the implementation of Particle Swarm Optimization (PSO) algorithm to artificial neural modeling in order to determine the ripeness and unripeness of citrus suhuensis. 200 citrus were being experimented from 1000 raw samples they were divided into ripeness and unripeness. The visible spectrometers were used from 445nm until 609nm based on yellow, green and orange color. From the range, only 30 identified wavelengths were selected for each sample’s input for the experiment. There training set was used to train in designing the best optimized connections’ weights using PSO. The algorithm has produced new weights during the training phase. When validated with the testing set, the best optimization model achievement is when the hidden layer size is 20 neurons. At this stage, the highest overall accuracy is recorded as 70.5% respectively based on 0.7 threshold. Also, the sensitivity and specificity is 61% and 80% respectively. It can be concluded that this model could recognized better a non-ripeness of citrus compared to ripeness.

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