RECOGNIZING THE RIPENESS OF BANANAS USING ARTIFICIAL NEURAL NETWORK BASED ON HISTOGRAM APPROACH

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Abstract— **The main objective of this project is to develop a technique to classify the ripeness of bananas into 3 categories, which is unripe, ripe and overripe systematically based on their histogram RGB value components. This system involved the process of collecting samples with different level of ripeness, image processing and image classification by using artificial neural network. Collecting bananas sample is done by using Microsoft NX6000 webcam with 2 mega pixels. 32 samples were used as training samples for artificial neural network. In order to see whether the method mention above can classify the image correctly, another 28 images was used as a testing. From the result obtained, it was shown that the artificial neural network can generally classify the ripeness of bananas. This is because it can classify up to 25 samples correctly out of 28 samples. Developing a program totally by using Matlab version 7.0 can help classification process successfully.**

Keywords – Ripeness, histogram, RGB, Artificial Neural Networks (ANN), bananas

I. INTRODUCTION

The use of computers to analyze images has many potential for agricultural tasks. There are many processes in agriculture where decisions are made based on the appearance of the product. Applications for grading the fruit by its ripeness, quality or size are based on its appearance [1].

Various ripeness techniques are being used for real-time authentication, the most popular ones being using mean of RGB identification [2].

Method on identifying ripeness of bananas by distinguishes the hue and color intensity of the color using image processing is tough, in detecting the ripeness of the different types of bananas. Furthermore, exists some "similar" color between the ranges of ripeness on the bananas, example from unripe and ripe [1]. Skin color that covered bananas that was not uniformly also given big problem in detecting the ripeness of the bananas [3].

A. Artificial Neural Network (ANN)

ANNs are composed of nodes that are modeled after neurons, with weighted links interconnected the units together.

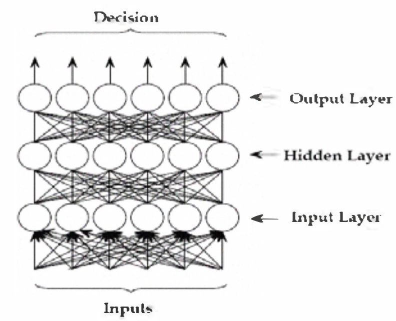

Fig. 1: Neural Network Architecture

The main difference between ANNs and other learning mechanisms is that it is composed of these simple units and they work together in a highly parallel manner. The Neural Networks have many algorithms that specify how this network should work [4].

An ANN is a computer model of the biological brain. It comprises [5]:

- A set of processing units
- A state of activation
- An output function for each unit
- A pattern of connectivity among units
- A propagation rule for propagating patterns of activities through the network
- An activation rule for combining the inputs impinging on a unit with the current state of that unit to produce a new level of activation for the unit
- A learning rule whereby patterns of connectivity are modified by experience
- An environment within which the system must operate

Net functionality or overall function achieved is determined by:

- the network topology
- individual characteristics
- learning/training strategy

- Training data.

B. *Neuron*

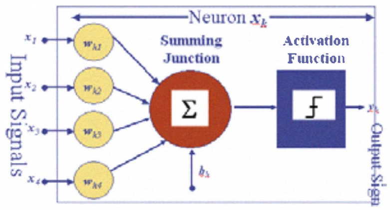

Fig. 2: Schematic for an electronic neuron

The model based on the biological neuron which is found in the brain. Basic neuron performs a weighted sum on its inputs and compares this to its internal threshold level. If the threshold is exceeded the neuron shall turn on. This system is known as a feed forward. Neuron takes the first input and multiplies it by the weight on that input line, and so on for each input [5].

C. *Learning Rules*

Learning rule is important to modify the weights and biases of a network. It is applied to train the network to perform some particular task. It falls into two broad categories: supervised learning, and unsupervised learning [2][5].

In supervised learning, the learning rule is provided with a set of examples (the training set) of proper network behavior where an input to the network is, and is the corresponding correct (target) output. As the inputs are applied to the network, the network outputs are compared to the targets. The learning rule is then used to adjust the weights and biases of the network in order to move the network outputs closer to the targets. In unsupervised learning, the weights and biases are modified in response to network inputs only. There are no target outputs available [5].For this paper, supervised learning is used.

D. *Multi layer Perceptron*

Multi-layer networks use a variety of learning techniques. The most popular was back- propagation [5]. This technique has been chosen for this research. The output values are compared with the correct answer to compute the value of some predefined error-function. By various techniques the error is then feed back through the network. Using this information, the algorithm adjusts the weights of each connection in order to reduce the value of the error function by some small amount. After repeating this process for a sufficiently large number of training cycles the network will usually converge to some state where the error of the calculations is small. In this case the network has learned a certain target function [6].

II. SCOPE OF WORK

The scope of work for this research can be summarized as in Figure 3.

Fig. 3: Scope of works.

III. COLLECTING SAMPLE AND IMAGE PROCESSING

The process of collecting samples and processing images should be done properly in order to ensure the classification process successful.

A. *Capturing An Image*

This project begins with collecting 3 sets of the unripe, ripe and overripe of bananas images. Each set of the classes contain 20 images. These samples of banana were taken using Microsoft NX6000 webcam and were saved in JPEG format.

Fig. 4: Images of unripe banana

Fig. 5: Images of ripe banana

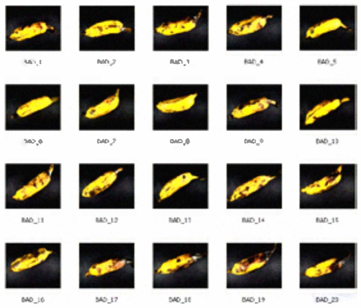

Fig. 6: Images of overripe banana

B. Image Resizing

Image taken was too big in dimension with resolution 352X288. So resizing of image was needed.

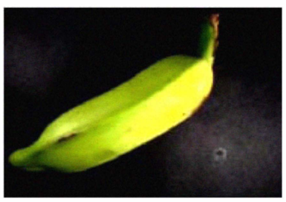

Fig 7: Original Image

Fig. 8: Resized Image

C. Extraction of RGB Component

As an alternative, the range of true pixel color which is from 0 to 255 was divided into 3 groups of intensity when plotting the histogram.
The first intensity 0-120 was grouped to 0; the second intensity 121-190 was grouped to 122 and the third intensity 191-255 was grouped to 255. The process of counting number of pixel will continue until it reaches total number of pixels for each RGB component.
Number of pixel that is counted are taken and saved into Microsoft Excels as an input training data to Artificial Neural Network. Since the RGB range was divided into 3 groups of intensity, each image will have 3 values of intensity for each component of R, G and B. Histogram shown in figure 9, figure 10 and figure 11 represent the intensity of each RGB color element. X-axis and y-axis show the number of pixels in each color group of intensity respectively

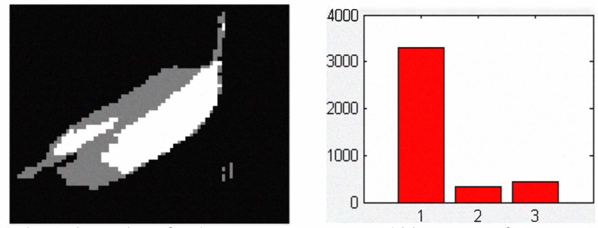

Fig. 9: intensity of red color component and histogram of Bananas

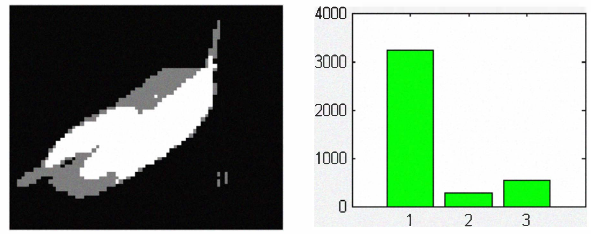

Fig. 10: Green color component and histogram of bananas

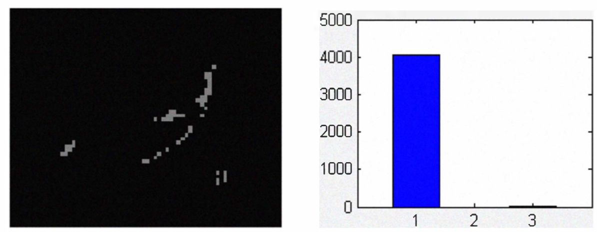

Fig. 11: blue color component and histogram of bananas

IV. TRAINING AND TESTING DATA

The training of an Artificial Neural Network using back-propagation method net involves 3 stages:

- Feed-forward of the input training pattern
- Back-propagation of the associated error
- Weight adjustment.

After the network has been trained, its application involves only the feed-forward phase. A multilayer net can learn only input patterns to an arbitrary accuracy. More than one hidden layer can also be used while one is sufficient. The weight adjustment is based on the gradient descendent method which minimizes the total squared error of the output of the network.

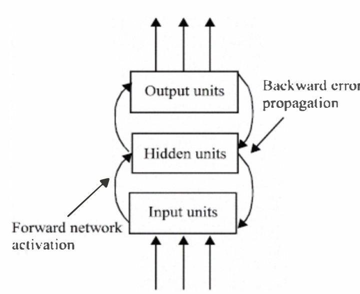

Fig. 12: Back-propagation Algorithm

During training, the net output is compared with the target value and the appropriate error is calculated. From the error, the error factor is obtained which is used to distribute the error back to the hidden layer. The weights are updated accordingly. In a similar manner, the error factor is calculated and the weights are updated simultaneously.

A. *Graphical User Interface (GUI) using MATLAB*

GUIDE automatically generates an M-file that initialized the GUI and contains a framework for the GUI callbacks the routines that execute in response to user-generated events. Using the M-file editor, codes were added to the callbacks to perform the functions. Figure 13 shows the GUI layout for Recognizing the Ripeness of Bananas Using Artificial Neural Network Based on Histogram Approach.

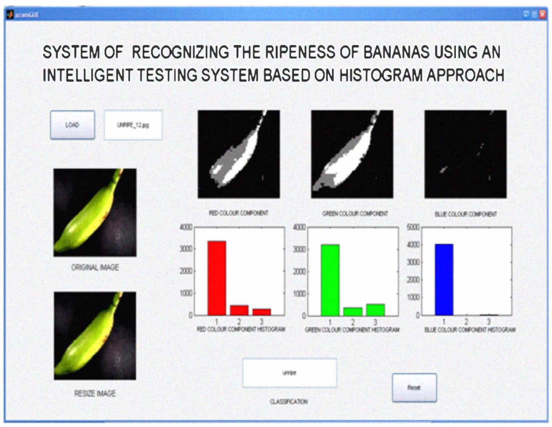

Fig. 13: GUI layout

V. METHODOLOGY

The whole process of determining the ripeness of bananas can be simplified as Fig. 14 below.

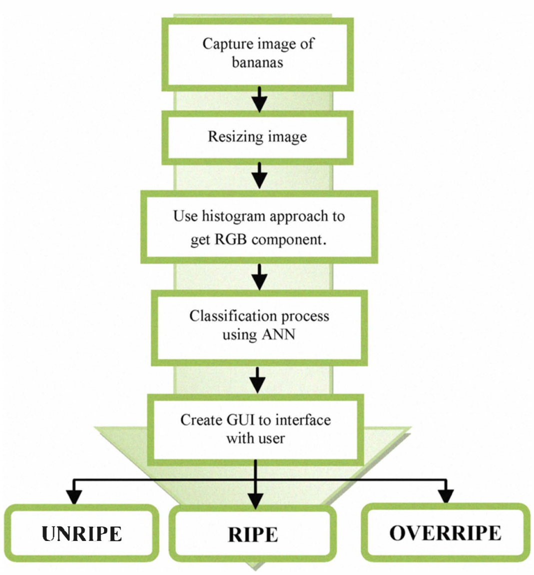

Fig. 14: Flow chart of the project development

VI. RESULTS AND ANALYSIS

The color intensity for RGB components for each training sample can be shown as below:

TABLE I UNRIPE BANANAS SAMPLE

	R			G			B		
Sample	**r1**	**r2**	**r3**	**g1**	**g2**	**g3**	**b1**	**b2**	**b3**
UNRIPE_1	3349	289	422	3283	232	545	4058	0	2
UNRIPE_2	3282	278	500	3242	179	639	4041	0	19
UNRIPE_3	3366	353	341	3300	323	437	4058	0	2
UNRIPE_4	3411	272	377	3261	349	450	4058	0	2
UNRIPE_5	3400	289	371	3300	311	449	4055	0	5
UNRIPE_6	3445	239	376	3309	278	473	4051	0	9
UNRIPE_7	3299	334	427	3225	291	544	4053	0	7
UNRIPE_8	3295	309	456	3233	344	483	4059	0	1
UNRIPE_9	3333	327	400	3261	292	507	4055	0	5
UNRIPE_10	3404	258	398	3307	238	515	4055	0	5

TABLE II RIPE BANANAS SAMPLE

	R			G			B		
Sample	**r1**	**r2**	**r3**	**g1**	**g2**	**g3**	**b1**	**b2**	**b3**
RIPE_1	3463	80	517	3507	116	437	4029	0	31
RIPE_2	3470	44	546	3499	73	488	4041	0	19
RIPE_3	3386	80	594	3428	107	525	3978	0	82
RIPE_4	3436	63	561	3469	85	506	4029	0	31
RIPE_5	3398	65	597	3440	85	535	4059	0	1
RIPE_6	3397	73	590	3432	116	512	4050	0	10
RIPE_7	3395	79	586	3429	95	536	4053	0	7
RIPE_8	3433	50	577	3464	72	524	4009	0	51
RIPE_9	3421	63	576	3466	90	504	4057	0	3
RIPE_10	3448	64	548	3504	67	489	4051	0	9
RIPE_11	3411	77	572	3475	83	502	4046	0	14
RIPE_12	3412	62	586	3450	84	526	4052	0	8

TABLE III OVERRIPE BANANAS SAMPLE

	R			G			B		
Samples	**r1**	**r2**	**r3**	**g1**	**g2**	**g3**	**b1**	**b2**	**b3**
BAD_1	3447	93	520	3548	144	368	4057	0	3
BAD_2	3354	107	599	3437	127	496	4049	6	5

BAD_3	3450	130	480	3548	127	385	4051	7	2
BAD_4	3393	127	540	3502	190	368	4047	0	13
BAD_5	3485	70	505	3539	76	445	4049	0	11
BAD_6	3433	84	543	3499	107	454	0	4060	0
BAD_7	3412	88	560	3479	166	415	0	4060	0
BAD_8	3363	101	596	3436	128	496	4052	0	8
BAD_9	3459	108	493	3536	147	377	4032	27	1
BAD_10	3417	113	530	3517	118	425	0	4060	0

r1, r2, r3, g1, g2, g3, b1, b2 and b3 from the 3 groups were set as an input for training data.

A. Optimization Process

The optimization process was applied in order to choose the smallest Mean Squared Error (MSE) value. In optimization process, trial and error concept was used to find the most suitable number of hidden nodes, value for momentum, **b** and learning rate, **a**. Results can be shown in the Table IV, V and Table VI. From the results, the 7 hidden nodes were chosen since the smallest value of MSE was achieved. The same goes to learning rate and momentum. Value for learning rate and momentum were chosen based on the lowest MSE produced.

NO OF HIDDEN NODES	MSE
1	performance goal was not met.
2	0.00726218
3	0.00834852
4	0.00908494
5	0.00987740
6	0.00710082
7	0.00393285
8	0.00821154

TABLE V: The optimization for momentum, b with 7 hidden nodes and learning rate, a is fixed at 0.1

a	b	MSE
0.1	0.75	0.00895602
0.1	0.8	0.00942001
0.1	0.85	0.00641239
0.1	0.9	0.00194646
0.1	0.95	0.00565568
0.1	1	0.00863989

TABLE VI: The optimization for learning rate, a with 7 hidden nodes and momentum is fixed 0.9

a	b	MSE
0.1	0.9	0.00194646
0.2	0.9	0.00488890
0.3	0.9	0.00675963
0.4	0.9	0.0097609
0.5	0.9	0.00783415
0.6	0.9	0.00691126

Training data set was used in optimization process in order to determine number of hidden nodes, learning rate and momentum using MSE analysis. Figure 15 shows the performance of the network using 7 hidden nodes, while learning rate and momentum equal to 0.1 and 0.9 respectively.

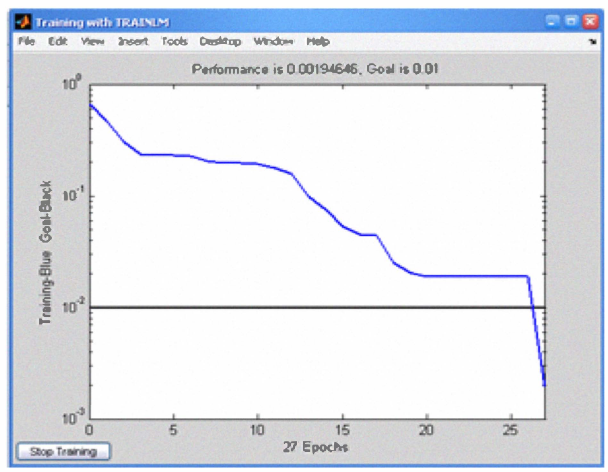

Fig. 15: Mean Square Error versus Epoch for Data Training of Tangent Sigmoid Function
Node 7, a=0.1, b=0.9

B. Result for testing samples

Table VII shows the classification result for testing samples.

TABLE VII: Classification result

Test Sample	ANN Target	ANN Actual	Result
UNRIPE_11	0 0 1	1 0 1	Cannot be classified
UNRIPE_12	0 0 1	0 0 1	Unripe
UNRIPE_13	0 0 1	1 0 0	Overripe
UNRIPE_14	0 0 1	0 0 1	Unripe
UNRIPE_15	0 0 1	0 0 1	Unripe

UNRIPE_16	0 0 1	0 0 1	Unripe
UNRIPE_17	0 0 1	0 0 1	Unripe
UNRIPE_18	0 0 1	0 0 1	Unripe
UNRIPE_19	0 0 1	0 0 1	Unripe
UNRIPE_20	0 0 1	0 0 1	Unripe
RIPE_13	0 1 0	1 0 0	Overripe
RIPE_14	0 1 0	0 1 0	Ripe
RIPE_15	0 1 0	0 1 0	Ripe
RIPE_16	0 1 0	1 0 0	Ripe
RIPE_17	0 1 0	0 1 0	Ripe
RIPE_18	0 1 0	0 1 0	Ripe
RIPE_19	0 1 0	0 1 0	Ripe
RIPE_20	0 1 0	0 1 0	Ripe
BAD_11	1 0 0	1 0 0	Overripe
BAD_12	1 0 0	1 0 0	Overripe
BAD_13	1 0 0	1 0 0	Overripe
BAD_14	1 0 0	1 0 0	Overripe
BAD_15	1 0 0	1 0 0	Overripe
BAD_16	1 0 0	1 0 0	Overripe
BAD_17	1 0 0	1 0 0	Overripe
BAD_18	1 0 0	1 0 0	Overripe
BAD_19	1 0 0	1 0 0	Overripe
BAD_20	1 0 0	1 0 0	Overripe

VII. DISCUSSION

Referring to Table I, unripe bananas has higher intensity at g3 component compared to component R and B. But when it getting ripe, (Table II) R (r3) component will increase and faintly having the same value as component G (g3). For overripe banana, the R (r3) component having the highest value while G (g3) component getting low.
The bananas that cannot be classified are most probably due to luminance effect of the sample image because the captured images were not taken under control condition.

VIII. CONCLUSION AND FUTURE WORK

The ripeness of bananas identification system using artificial neural network based on histogram approach that has been develop was successful. This system is applicable to recognize the ripeness of bananas based on three groups of color intensity shown in histogram. The background of the images and luminance effect also played an important role in recognizing the ripeness of bananas. In order to overcome this problem, the sample should be captured under control condition. From the result obtained, it can be concluded that the system give the best performance when there are 7 hidden nodes, learning rate fixed at 0.1 while momentum at 0.9. It was shown that the artificial neural network can generally classify the ripeness of bananas. This is because it can classify up to 25 samples correctly out of 28 samples.
In order to increase the effectiveness of this classification system, a few suggestions are recommended:

- Using high pixel digital camera.
- Eliminate the background using edge detection and select only the main object.
- Better processor and computer specifications since the color resolution and processing time totally relies on the processor used.
- Develop the whole system including capturing the images in real time and link it directly to the developed system.
- Increase number of color intensity group for better accuracy.

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