Assessment of Lettuce (*Lactuta sativa*) Crop Health Using Backpropagation Neural Network

Ira C. Valenzuela,[1,]* Argel A. Bandala,[2] and Elmer P. Dadios[2]

***Abstract* — The determination of the healthiness of a crop is relevant in ensuring a high agricultural yield. The growth rate and the productivity are the factors that can help to establish the expected yield. This is done by computing the crop assessment index. The main objective of this study is to develop a simple color recognition algorithm using digital image processing techniques. This will eliminate subjectiveness in the classification of healthy and unhealthy lettuce. Moreover, this can help the farmers to assess the quality of the crops while growing them. The crop used in this study is romaine lettuce. The image processing was built using LabView Vision Assistant through RGB acquisition. The backpropagation of the artificial neural network was used to increase the efficiency of the system in assessing the quality of the lettuce. The total number of images used in the study is 280 wherein 15% were used for validation, 15% were used for testing, and 70% were used for training. The developed system proves to provide a better assessment of the lettuce crop health.**

Keywords: **lettuce, crop health assessment, ANN, backpropagation**

I. Introduction

The features that can determine the crop yield are its health and its seasonal progress. These are critical characteristics and are early indicators of the possible amount of crop yield, crop risk, and the degree of success or failure [1]. The determination of the healthiness of a crop is relevant in ensuring a high agricultural yield. The conceivable stresses that will cause low yield must be mitigated by the farmers at the early stage of the crop growth. Examples of these stresses are the parasite infestations, moisture deficiencies, and weed infestations. Growth rate and productivity are the factors that can help to establish the expected yield. This is done by computing the crop assessment index.

Traders of agricultural products are not usually in the field to personally monitor the growth and crop yield. They generally rely on the crop assessment index and other data that the farmers are giving to them in setting the price of the crops. These data are used for worldwide negotiation of trade agreements [2]. Also, this can help to locate future problems like the famine in Ethiopia. A significant drought was experienced during the 1980s and devastated a lot of crops. Humanitarian aid and relief efforts will be facilitated in advance when it is forecasted early [3].

The traditional way of assessing the crops' health is by visual inspection of its physical features. Possible diseases infecting the crops are seen through the discoloration on its surface. Also, the nutrient contents are measured in laboratories to check if these are sufficient [4]. Current technologies such as [5][6] involve the measurement of normalized differential vegetation index (NDVI). Hyperspectral images are captured and processed in a software [7][8][9]. These are done for large vegetation areas. In one study, the researcher proposed that to improve the color image feature, image normalization is done through color transfer process. The condition is that the data set should be uniform [10][11].

In this study, the crop to be modeled is a lettuce. *Lactuta sativa L*. or commonly known as lettuce as shown in Figure 1 is one of the most important salad crops and is grown worldwide. It originated from Asia. It can grow best in temperatures 45°F–80°F. It can also grow in hotter weather but for short intervals and taste bitter [12]. There are seven types of lettuce, but for this study, the romaine type of lettuce will be studied.

Fig. 1. Romaine lettuce.

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The main objective of this study is to develop a simple color recognition algorithm using digital image processing and pattern recognition. This will eliminate subjectiveness in the classification of healthy and unhealthy lettuce. Moreover, this can help the farmers to assess the quality of the crops while growing it.

The rest of the paper is organized as follows: Section II explains how to extract the features and their analysis. This includes the data acquisition and experimental setup. Section III explains the structure of the network, the input and the output, and the criteria for the network. In Section IV, the data obtained from the training, validating, and testing are discussed. Finally, Section V gives conclusions.

II. Feature Extraction and Analysis

Figure 2 illustrates the block diagram of the system. It consists of the different methods applied to obtain the desired output. The preprocessing is done on LabVIEW software.

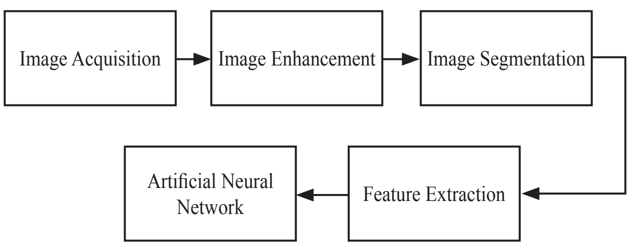


Fig. 2. Block diagram of the system.

A. Image Acquisition

Two hundred eighty (280) images of lettuce are gathered. These images include the quality classifications good and reject.

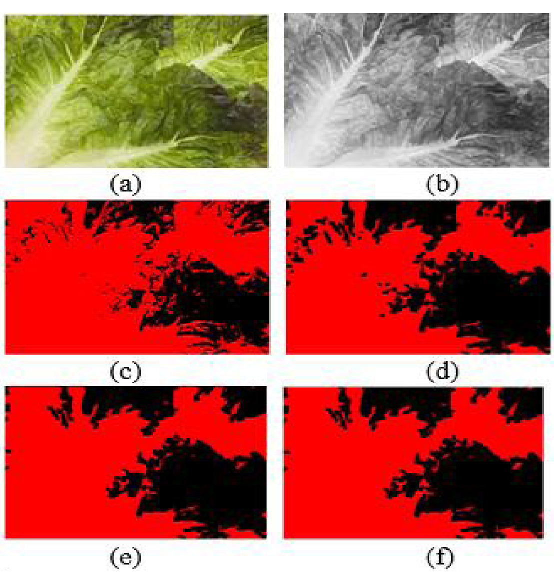


Fig. 3. Image processing of the sample lettuce leaf.

B. Image Enhancement

The purpose of enhancing the image is to reduce the noise present in the image and to adjust the image contrast. Color space conversion has been done also through translating the RGB values into HSV values. This is illustrated in Figure 3b. The image color is converted into HSV because of its similarity with the human eye perception. This is the mostly used color model in high-end image processing. The RGB color model is based on the three independent color planes, namely, red, green, and blue. And to state a certain color is to specify the amount of RGBs present on that particular color. On the other hand, the HSV color model is composed of hue, saturation, and value. The hue is measured from the red color, and saturation is the distance from the axis. This is shown in Figures 4a and 4b.

Figure 5a shows the actual image of the sample lettuce, while Figure 5b shows the separation of background image and foreground image. Figure 6a shows the RGB image of the lettuce, while Figure 6b shows the HSV image.

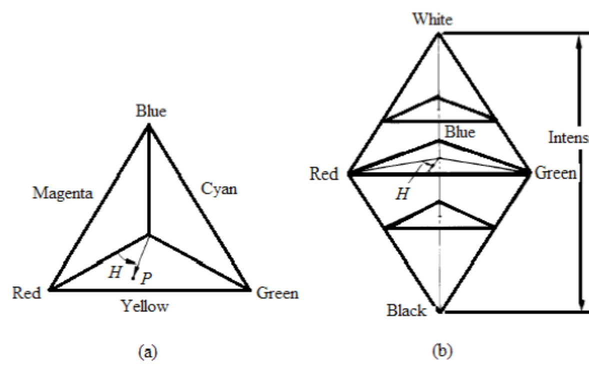


Fig. 4. (a) HSV color triangle and (b) HSC color solid.

Fig. 5. (a) Sample lettuce (actual image) and (b) background and foreground separation images.

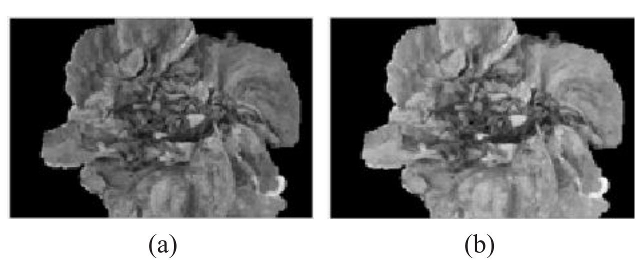


Fig. 6. (a) RGB image and (b) HSV image.

The saturation and value have a range of 0–1. Zero (0) represents the black color while one (1) represents the white color. This is commonly used because of its ability to generate high-quality images. Saturation refers to the grayness of a color, and value refers to the brightness of the color. The RGB has been normalized using equation 1. The normalized HSV can be computed using equations 2, 3, 4, and 5.

$$r = \frac{R}{R+G+B};\ g = \frac{G}{R+G+B};\ b = \frac{B}{R+G+B} \quad (1)$$

$$h = \cos^{-1}\left\{\frac{0.5[(r-g)+(r-b)]}{\sqrt{(r-g)^2+(r-b)(g-b)}}\right\} \quad h \in [0,\pi]\ for\ b \le g \quad (2)$$

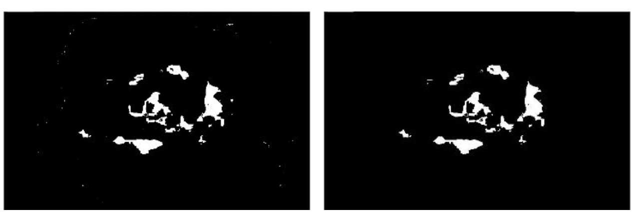
$$h = 2\pi - \cos^{-1}\left\{\frac{0.5[(r-g)+(r-b)]}{\sqrt{(r-g)^2+(r-b)(g-b)}}\right\}\ h \in [\pi, 2\pi]\ for\ b > g \quad (3)$$

$$s = 1 - 3 \cdot \min(r, g, b);\quad s \in [0,1] \quad (4)$$

$$v = \frac{R+G+B}{3 \cdot 255};\quad v \in [0,1] \quad (5)$$

C. Image Segmentation

Figures 3c to 3f show how the image is segmented. This was done through setting a certain threshold and placing a mask. The image was then converted into black and white components to become a binary-level image. Figure 7a shows the binary image with noise. The small white components or blobs visible in the image are called noise. In Figure 7b, the noise was removed and retained only the defect.



(a) (b)

Fig. 7. (a) Binary image (with noise) and (b) binary image (with defects).

D. Feature Extraction

To analyze the crop health of the lettuce, two parameters are extracted: (1) pixel area and (2) percent area/image area. The optimal performance of the ANN was achieved because of the heuristic analysis of the network.

III. Artificial Neural Network (ANN)

ANN is one of the commonly used computational models. It is patterned in the biological neural system of a mammal but in a smaller scale [13]. The layers of the neural network are composed of input, hidden, and output. The organization of these layers makes the network highly capable of predicting the outcomes with high accuracy. The backpropagation algorithm is added in this to provide a high accuracy and versatility in recognizing the defects in the lettuce crop base on their colors. The neural network served as the medium for identifying the quality of the lettuce.

A. Backpropagation Algorithm

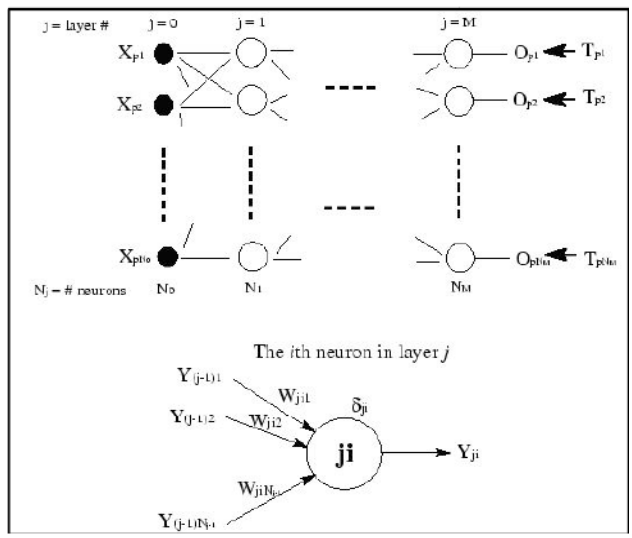


Fig. 8. Multilayer network of backpropagation ANN.

Equation 6 shows the Widrow–Hoff delta learning rule, which is the foundation of the backpropagation algorithm.

$$w = w_{old} + \eta\delta x \quad (6)$$

where $\delta = y_{target} - y$ and η is a constant that controls the learning rate (amount of increment/update Δw at each training step) [14].

Random prediction of outcome is initially made by neural network with the presented patterned images. With the delta leaning rule, adjustment of weights for improved performance becomes possible. It can predict the data correctly. This is repeatedly presented to the neural nets to minimize the error.

B. Design Architecture

The neural network was created in different combinations, with two input nodes, one hidden layer with varying number of hidden nodes for each training, and one output node. Both the hidden and output layer neurons were activated by binary sigmoid activation function.

The basic training algorithm adjusts the weights in the steepest descent direction (negative of the gradient) [15]. However, it was later discovered that this process does not necessarily produce the fastest convergence. Hence, in this study, the scaled conjugate gradient algorithm (SCG) of [16] was used as the training algorithm. SCG avoids time consuming line search per learning iteration thus providing faster training with excellent test efficiency.

C. *Training and Classification*

The output is 1 if the lettuce has a good quality and no defect and 0 if the lettuce has defects. Two hundred eighty (280) images were extracted and divided into three sections. Of the images, 70% were used for training, 15% were used for testing, and the remaining 15% were used for validation. At the start of the training, weights and biases were randomly initialized. Also, the images were being inputted in a sequential manner. It was repeated until the required training number is obtained.

Three stopping criterions were set for the training of the network, that is, when the maximum iteration, minimum gradient, and maximum validation checks are reached. When these were reached, the neural network can be used for the quality assessment of the lettuce.

IV. RESULTS AND DISCUSSION

A. *Training*

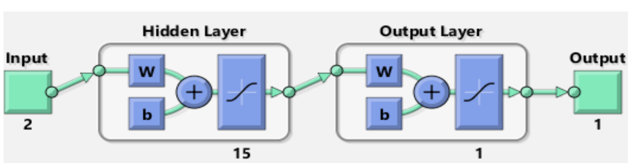


Fig. 9. Neural network architecture.

Figure 9 shows the architecture used for the neural network of the system. It is composed of two input layers, one hidden layer with 15 neurons, and one output layer.

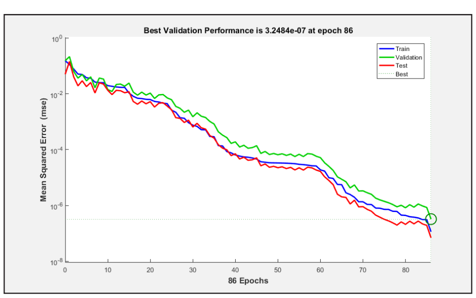


Fig. 10. Performance plot.

Figure 10 shows the performance plot of the trained neural network. For this training, the minimum required gradient was set to 1e-06. When the gradient has reached this value, the training has stopped at epoch 86 with a cross entropy value of 7.6814e-07. Good classification of the system is provided by the minimum cross entropy value.

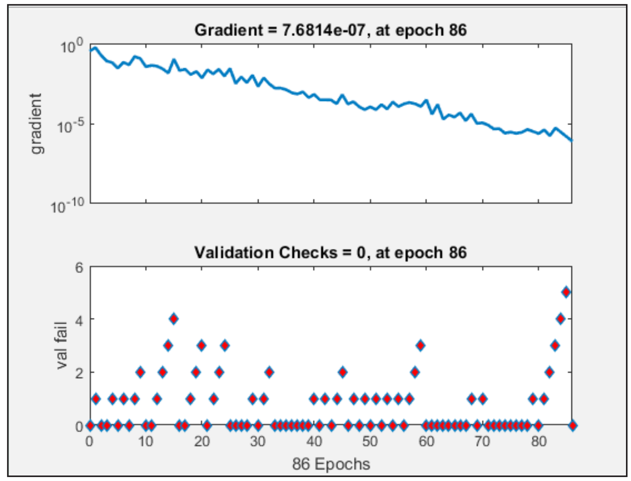


Fig. 11. State plot of lettuce health assessment.

In updating the values of the weights and biases, the gradient is used. The state plot for the training is shown in Figure 11. It illustrates the changes in the gradient value with respect to the epoch and the validation checks. For the 0th validation check, the gradient value is 7.6814e-07. The validation check ensures that the mean square error of the validations stops to decrease.

B. *Testing*

The traditional way of inspecting the defects in lettuce through visual gives a relatively high error due to different visual perceptions and lighting conditions. The use of the machine vision system with ANN has been studied to be an alternative way or the easiest way in identifying the quality of lettuce.

For the testing of the trained neural network, 20 samples are collected and used. The inputs of the system are the extracted values of RGBHSV components of the lettuce image. The actual classification of the samples is given as good (0) and reject (1). The N1 and N2 in output subheading of Table 1 correspond to the neuron 1 and neuron 2, respectively.

Figure 12 shows the comparison of the ANN output and actual value of the samples. With the 20 samples, a small difference was observed.

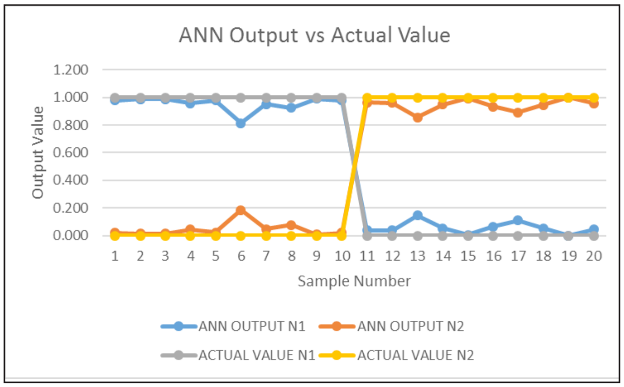


Fig. 12. Comparison of ANN output and actual value.

The relative error plot between the two outputs is shown in Figure 13. It is computed using equation 2. Relative error shows how good a measurement relative to the sample size is and is the ratio of the absolute error and the absolute value. It is important to determine the relative error to show how close the obtained data are to the target data. With the given samples, the mean relative error is 0.051.

$$Relative\ Error = \frac{Absolute\ Error}{Absolute\ Value} \tag{7}$$

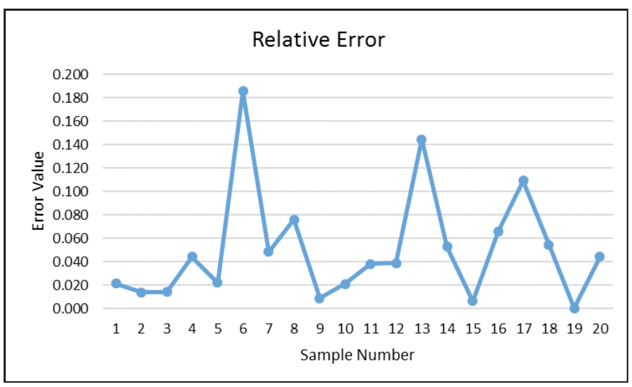


Fig. 13. Relative error plot.

V. Conclusion

The application of backpropagation neural network was successfully done on the assessment of lettuce crop health based on its color. RGB components of each image were obtained using RGB color feature extraction in LabVIEW. Based on the result, the system is capable of assessing the health of the lettuce with a minimum square error of 3.2484e-07.

Acknowledgment

The authors would like to acknowledge the financial support of the Department of Science and Technology–Engineering Research and Development for Technology.

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