International Journal of Engineering & Technology, 7 (4) (2018) 4271-4277

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET
doi: 10.14419/ijet. v7i4.17421
Research paper

Lettuce cultivation period modelling: an image processing and neuro-fuzzy based approach

Ira C. Valenzuela [1] *, Elmer P. Dadios [2]

[1] Department of Electronics and Communications Engineering, De La Salle University, Manila, Philippines
[2] Department of Manufacturing Engineering and Management, De La Salle University, Manila, Philippines
**Corresponding author E-mail: ira_valenzuela@dlsu.edu.ph*

Abstract

In this study, the cultivation period of a lettuce was modeled using image processing and neuro-fuzzy inference system. The images of the lettuce were acquired using a camera and were processed using OpenCV. Image features were extracted such as pixel count and RGB and then converted into HSV, CIELab and YCbCr. To select which among these colors best represents the lettuce image with respect to cultivation period, a feature selection algorithm was used. The YCbCr features and pixel count were chosen based on their correlation value. These data became the input for the neuro-fuzzy inference system. The system was modeled for hybrid optimization with the use of generalized bell-type membership function which is best for smooth nonlinear function. A total of 81 fuzzy rules were developed. Based on the result, the model was able to determine the cultivation period of a lettuce with a 99.96% accuracy.

Keywords: *Cultivation Period Modelling; Image Processing; Neuro-Fuzzy; Plant Growth Stage; Vision System.*

1. Introduction

Assessment of the quality of crops are essential on a wide variety of aspects, one for which is the analysis of the different aspects of information that the plant brings from its first stage to the last stage based for data analysis on the timeline of its growth. The procedure for crop growth and yield formation takes time accumulation. The models for the different crop growths can be used to precisely describe and measure crop growth and development, based on crop diversities, soil properties, weather conditions, and types of management. In order to characterize the soil-crop atmospheric system, these models frequently need a huge amount of input parameters [1]. Measurement is the first and primary step to consider in assessing the crop, since it forces objectivity. With many thousands of components to consider, structured measurement is the essential lead that will make you see things that otherwise you would miss at a quick glance [2]. Assessment based on the health of crops, are more concerned with detecting crop infestations, moisture deficiencies, insects, fungal, and weed infestations in order for its needed efficient agricultural productivity [3].

There are different techniques in analyzing essential approaches used for efficient assessment of crops with specific and accurate details in plant qualities for the whole crop yield growth development. Basically, one conventional technique that is simpler to use, but less accurate, is by using one's senses to assess problems and perceive patterns in the crop. Feeling, smelling, tasting and especially looking at the soil and crops will determine temperature, texture and quality of its soil and leaves [2]. Estimating the crop yield in numerous regions depend on their original way of strategies of information gathering for the evaluation of both crop and yield coming from field reports based on ground [4]. Conventional methods include the empirical-statistical model and crop growth model. The first one obtains the valuable parameter relating to the crop yield by an experimental equation, from which acquires the constant value of the factors individually. The second one shows the approximation of the yield of the crops as its composite collaboration of the unique physical processes with surroundings [5]. Remote sensing involves different attributes to monitor the health of the crops, which are the possibility to see beyond the visible wavelengths into the infrared which are very sensitive to crop vigor and crop stress and damage. They also require spatial overview of the land which allows the farmer to discern images of the field that permits easier handling of the crops [3]. As for the vision system, a distinctive number of techniques was used which provides increased quality and accuracy in its assessment. The first method offers a 3D approach rather than a 2D approach in image processing, which particularly uses a Red Green Blue – Depth (RGB-D) camera that operates by producing a 3D point-cloud from its captured depth map from the plant, or either a photometric stereo analysis that takes the picture of the plant with multiple light sources placed in recognized locations which produces a surface alignment from its reflected illumination [6]. Another method is by utilizing a special algorithm known as the hybrid artificial neural network-harmony search (ANN-HS) to separate numerous plants from their backgrounds in their distinctive stages of growth, distinctive day conditions and has a single regulated state with distinctive imaging conditions. Using the algorithm, distinctive classes were categorized, and a suitable color space were selected to threshold for every class, then the vision system was tested beneath field situations [7]. Lastly, a technique which involves the use of a color charge-coupled device (CCD) camera to distinguish leaf area of each seedling, registered to a fuzzy logic-based classifier and models the quality classification of each crop established from their growth pattern [8]. These techniques may provide enough efficiency, but it has some gaps. With the conventional methods often being expensive and time-wasting, they are also likely to have huge miscalculations. This is due to the fact that the ground inspections are often imperfect, which results to insignificant approximations and assessment of different yield of crops. The main problem is the provision of a more essential objective, consistent and potentially less expensive and more rapid strategies which can be utilized for supervision of the growth of crops with instant evaluation of its yield. By using the remote sensing method, it is proven to have the ability and aptitude by delivering spatial data all around the globe with the different feature, happenings or occurrences on the world taking place during its current process, which both can accomplish identification of crop classes and estimation of crop yields [5]. However, still, remotely sensed data can not reveal the intrinsic mechanism of crop development status and its correlation with environmental conditions [1].

In this study, the lettuce will be used as a study crop. Lettuce (Lactuca sativa) is a crop with succulent leaves that is commonly used in different foods, especially salads [9]. It grows at cold weather with an average daily temperature from 60ºF to 70ºF, which makes it ideal to be planted in late summer or early spring [10]. Lettuce is categorized according to its leaf or head formation. Crisphead or iceberg lettuce is described as having tight head of crisp leaves. Loose-leaf lettuce, or simply leaf, is a slow bolting and heat resistant variety of lettuce that does not form tight heads. Lastly, romaine lettuce is a tall and upright variety that has thick ribs and spoon-shaped leaves. Lettuce seeds are usually planted with the depth of one-fourth to one-half inches below the ground level. The germination of the lettuce seeds requires a temperature of 40ºF to 80ºF while its growth requires 60ºF to 65ºF [11].

The main objective of this study is to find a suitable and all-around technique on the measurement and assessment of crops from its growth development. An image processing technique will be used to capture the plant growth parameters. These will be the input to the neuro-fuzzy system model. And the output will be the predicted or forecasted cultivation period of the plant. In response, a robust method needs to be produced for a versatile system able to withstand any natural occurring circumstances in the environment. This includes the overall quality, characteristics and natural behavior of the crop during its growth stages with a wider range of the overview of the land that provides a more accurate, empirical and concise results.

2. Related studies

Image processing can be utilized in crop assessment. Determining growth levels and proper harvest time are a few examples of applications of image processing in the assessment of the crop. This study was conducted for the analysis and prediction of the growth of lettuce. The deep flow technique was utilized with the sprayed water culture system then processed the captured image. A CCD camera was used to capture the image through the use of image processing by means of a computer. Growth was observed at 48-hours interval. For the imaging algorithm, image processing was done through Microsoft Visual C++ 6.0. The captured image was binarized based on the Hue, Saturation and Light. Filtering was made to remove noise. As a result, the background of the lettuce was removed. Growth of lettuce was analyzed through pixels of lettuce, and was compared with growth-related data. Based on the results, it was concluded that image processing can be used in predicting the lettuce growth through image processing [12].

A study was conducted to monitor the growth of a Boston lettuce plant. A stereo-vision system was used to determine the plant features and construct panoramic images. Using image processing algorithms, geometric features such as the projected leaf area, plant height, volume and diameters were developed. Growth curves were determined using the extracted features from the plant. OpenCV library was used in the development of the image processing algorithm. The weight of the plant was obtained by mounting a load cell in the weight measurement instruments. Fresh weight is also analyzed in this study to demonstrate efficiency of the developed system. The process starts with the image acquisition; all raw images were saved in JPG format. The raw image then undergoes stitching to create a panoramic view. After stitching, background segmentation then feature extraction takes place. By applying threshold and GrabCut algorithm, the panoramic image background was segmented from plants area. The 2D plant features were calculated including the projected leaf area, width, length, maximum radii, and minimum radii. Results show that this study demonstrates the ability of image processing to determine plant measurements. Successful results have proved the feasibility and functionality of the system in monitoring the plant growth and feature measurement [13].

A machine vision system can be used for segmenting different plants using artificial neural network-harmony search (ANN-HS). It classifies different growth stages, conditions of the day, imaging situations, and one controlled state. The camera is mounted in the F-shape arm and a motor was used to make movement possible. The said system has two stages, one is for the photography state specification and the other stage is for applying an appropriate threshold. There are almost 24,000 images taken during the day from eight different states and one control state. In classification process, the Meta-heuristics and statistical classifiers were used. Five features were selected through hybrid artificial neural network – differential evolution algorithm out of 126 extracting features of five color spaces such as Red Green Blue (RGB), Cyan Magenta Yellow (CMY), Hue Intensity saturation (HIS), Hue Saturation Value (HSV), luma and chroma (YIQ and YcbCr). The results were desirable based on the observation during the day. In determining the threshold level for six states, it must be on the third channel related to the color space and the other threshold level should be determined in color spaces such as HSV and YIQ. It was concluded that different color spaces are important for choosing a feature that is best to use in the classifier. Hybrid artificial neural network-differential evolution algorithm method is better compared to the hybrid artificial neutral network genetic and particle swarm algorithm [7].

It is common in the previous researches that the machine vision is in the 2D approach. It can affect and limit the results by parallax, perspective, occlusion and changes in the background light especially in the field. In this study, 3D approach was used for the analysis of crop to utilize more accurate gathered data. At a very high resolution, the four-light photometric stereo can strongly recover 3D surface texture from crops. From an illuminated object with a constant view and different directions, a surface normal field was recovered. The photometric stereo can separate the 3D and 2D textures producing a good 3D quality surface and accurate color data aside from getting the surface shape and texture. It reflects the effect in hue or in the changes in pigmentation surface [6].

The germination and quality evaluation of the seed can be monitored in an automatic system using a vision system through fuzzy logic algorithm that is artificial. The said study identifies the seedling and leaf area with the Image processing system. The system used a color CCD camera to capture seeds that was planted on cells. The information enters to the Fuzzy Logic-based classifier and simulates the quality grading of seedlings based on their growth pattern. The system can develop many possibilities in decision making for the seed production industry because of the database provided. A mobile camera was installed in able to capture the image of different seed trays. The system measures the area of all the object in the image captured. It can also use for obtaining the relationship between the area of the tray and obtaining its size. In getting the image of the tray, image acquisition system can be used while in image processing can automatically calculate the leaf are of cotyledons. The said study used Fuzzy Logic as a classifier for determining the degree of development of the seedlings with a database containing important knowledge. Three horticultural crops were used including Lettuce and the Fuzzy Logic produced closer evaluations to the actual data that supported the algorithm used has a high reliability specifically for germination control [8].

3. Methodology

Loose leaf lettuce has three growth stages namely sowing, vegetative and harvest. In sowing stage, the seeds are planted in a seedling tray and placed in the nursery. The germination usually took 0-12 days. Then, the plant is grown until 20 days. Vegetative stage starts once the crop is transplanted. By this time, the crop is transferred in the environmental chamber where the lighting, water, temperature and NPK are controlled. Harvest stage happens between 45 - 65 days old of the lettuce.

Python programming with OpenCV library was used in this study to develop a feature extraction algorithm. The image will undergo preprocessing to remove the background before being subjected to feature extraction. In this study, 21 samples were used, 3 for each day at 5-day increment starting at Day-20.

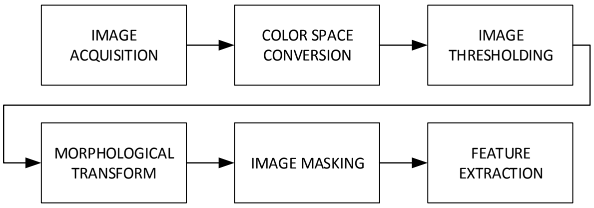


Fig. 1: Block Diagram of the System.

3.1. Image acquisition

First, the image of the lettuce was taken by an image capturing device. In this study a C922 Pro Webcam was used. It captures full HD (1080p) images and has autofocus capabilities. Images captured is saved in JPG format and is stored in a local storage.

3.2. Image processing for feature extraction

3.2.1. Color space conversion

In this section, the captured image was converted to CIEL*a*b* color space and grayscale. The grayscale image is used as the base image for the binary image [15] [16]. The a* value on the CIEL*a*b* color space shows distinct features for lettuce and is used as basis for the threshold value.

Given the chromaticity coordinates of an RGB system (x_r,y_r), (x_g,y_g) and (x_b,y_b) and its reference white (X_W,Y_W,Z_W), here is the method to compute the 3×3 matrix for converting RGB to XYZ:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = [M] \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{1}$$

Where

$$[M] = \begin{bmatrix} S_r X_r & S_g X_g & S_b X_b \\ S_r Y_r & S_g Y_g & S_b Y_b \\ S_r Z_r & S_g Z_g & S_b Z_b \end{bmatrix} \tag{2}$$

$$X_r = x_r / y_r \tag{3}$$

$$Y_r = 1 \tag{4}$$

$$Z_r = (1 - x_r\text{-}y_r)/y_r \tag{5}$$

$$X_g = x_g / y_g \tag{6}$$

$$Y_g = 1 \tag{7}$$

$$Z_g = (1 - x_g\text{-}y_g)/y_g \tag{8}$$

$$X_b = x_b / y_b \tag{9}$$

$$Y_b = 1 \tag{10}$$

$$Z_b = (1 - x_b\text{-}y_b)/y_b \tag{11}$$

$$\begin{bmatrix} S_r \\ S_g \\ S_b \end{bmatrix} = \begin{bmatrix} X_r & X_g & X_b \\ Y_r & Y_g & Y_b \\ Z_r & Z_g & Z_b \end{bmatrix}^{-1} \begin{bmatrix} X_W \\ Y_W \\ Z_W \end{bmatrix} \tag{12}$$

This conversion requires a reference white (X_r, Y_r, Z_r).

$$L = 116 f_y\text{-}16 \tag{13}$$

$$a = 500\left(f_x\text{-}f_y\right) \tag{14}$$

$$b = 200\left(f_y\text{-}f_z\right) \tag{15}$$

Where

$$f_x = \begin{cases} \sqrt[3]{x_r} & if\ x_r < \epsilon \\ \frac{\kappa x_r + 16}{116} & otherwise \end{cases} \tag{16}$$

$$f_y = \begin{cases} \sqrt[3]{y_r} & if\ y_r < \epsilon \\ \frac{\kappa y_r + 16}{116} & otherwise \end{cases} \tag{17}$$

$$f_z = \begin{cases} \sqrt[3]{z_r} & if\ z_r < \epsilon \\ \frac{\kappa z_r + 16}{116} & otherwise \end{cases} \tag{18}$$

$$x_r = \frac{X}{X_r} \tag{19}$$

$$y_r = \frac{Y}{Y_r} \tag{20}$$

$$z_r = \frac{Z}{Z_r} \tag{21}$$

According to CIE standard, a linear segment with a slope of κ is applied for relative luminance (x_r, y_r, z_r) below or equal to ϵ, where the relative luminance is near black [14].

$$\epsilon = \begin{cases} 0.008856 & Actual\ CIE\ standard \\ 216/24389 & Intent\ of\ the\ CIE\ standard \end{cases}$$

$$\kappa = \begin{cases} 903.3 & Actual\ CIE\ standard \\ 24389/27 & Intent\ of\ the\ CIE\ standard \end{cases}$$

Based on the converted color spaces, a binary image was created. The a* value of the CIELAB distinctly shows green colors much darker while the color brown will show lighter, a threshold value is set based on the lowest value of the a* component in the leaf area of the lettuce. The resulting image is a binary image with the background set as 0 and the plant set as 1.

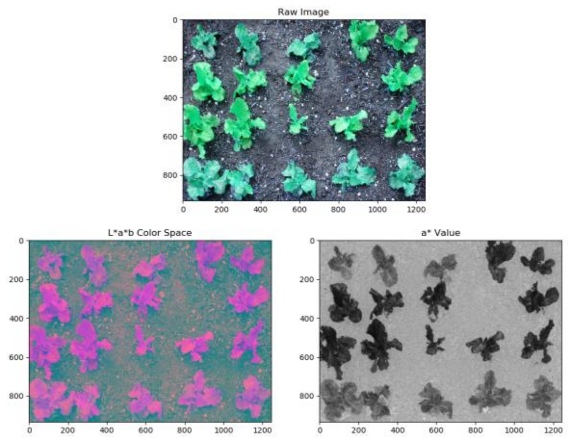


Fig. 2: Converted Color Space.

3.3. Image thresholding

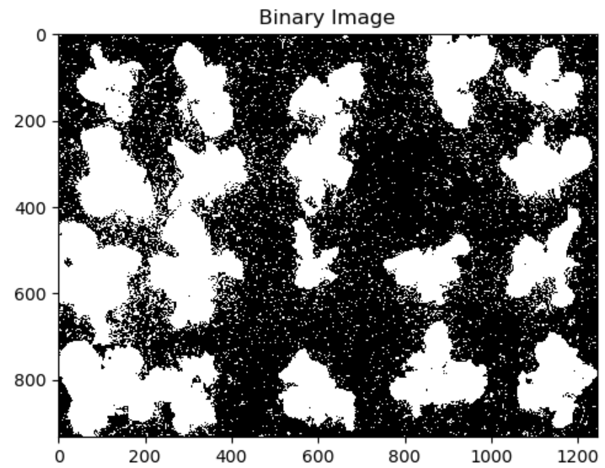


Fig. 3: Binary Image.

3.2.2. Morphological transform

The binary image created was filtered using morphological transformations to remove noise. A kernel value at 3x3 pixels was set, the selected value removes the noise while keeping the lettuce intact. Then through erosion process, a pixel either 1 or 0 will be considered 1 only if all the pixels under the kernel is 1, otherwise it is eroded. This will remove noise in the picture however, erosion shrinks the object area. To counter the decrease in area, dilation takes place, it is the opposite of erosion. It increases the white region in of the image [17] [18].

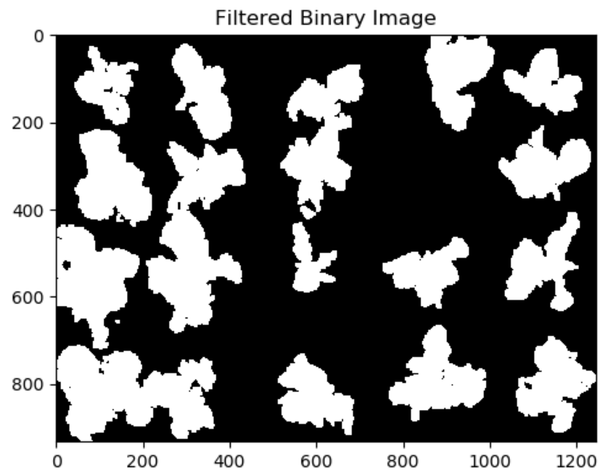


Fig. 4: Filtered Binary Image.

3.2.3. Image masking

In this section, the filtered binary image will be masked with the raw image. A final image will be created with the background removed and will be subjected to feature extraction.

3.2.4. Feature extraction

In this section, the mean RGB, HSV, CIEL*a*b*, YCbCr and pixel count of the masked image is extracted.

3.3. Neuro-fuzzy design

Figure 6 displays the fuzzy inference system used in this study. Each component of the Y, Cb, Cr was used together with the pixel count for inputs and the output is the cultivation period of lettuce.

Figure 7 depicts the membership function for the all the inputs of the neuro-fuzzy system. It has three levels namely: low, medium, high. Generalized bell was used because their properties are more suitable to model the possibility distributions. Also, it is one of the smooth nonlinear function whose derivatives are continuous.

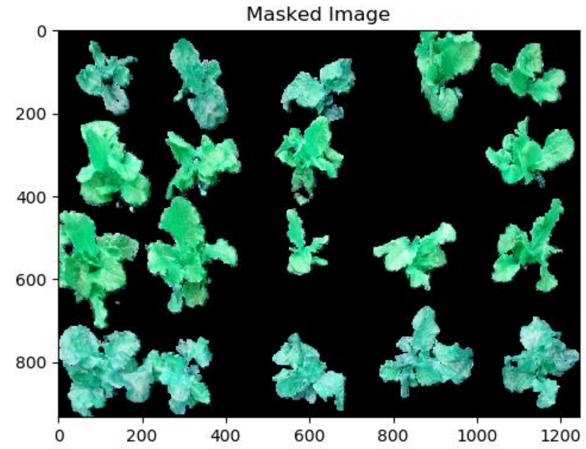


Fig. 5: Masked Image.

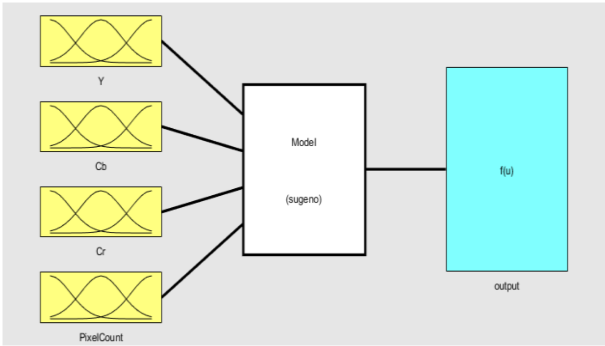
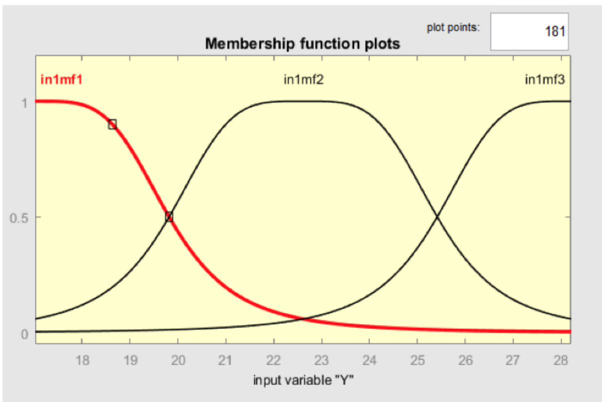
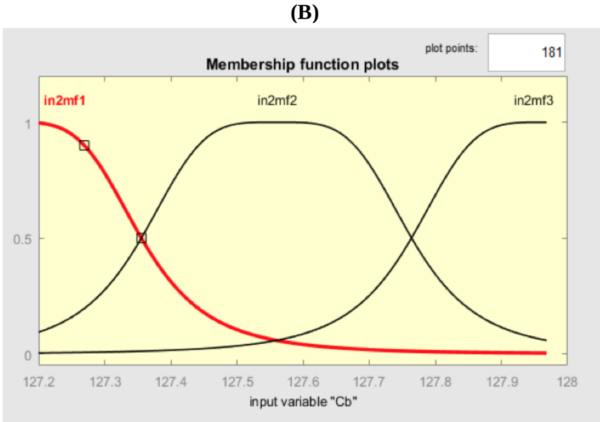


Fig. 6: Four-Input Fuzzy Inference System.

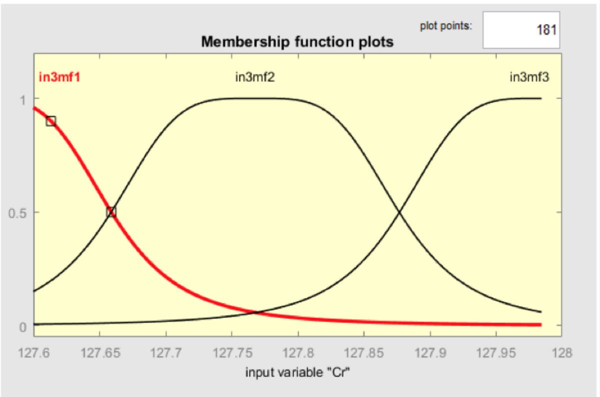
(A)



(B)



(C)



(D)

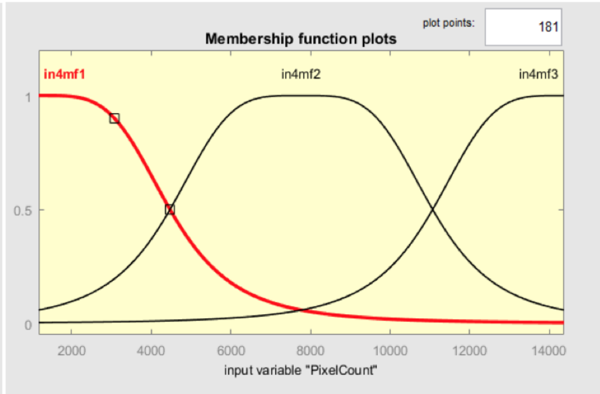


Fig. 7: Membership Function of (a) Y Input , (b) Cb Input, (c) Cr Input and (d) Pixel Count.

Figure 8 shows the neuro-fuzzy model structure. It is modeled based on the number of input membership functions. inputmf corresponds to the membership function of the input while outputmf corresponds to the output membership functions.

Table 1 shows the training parameters for the system.

Table 1: Neuro-Fuzzy Training Parameters

Item	Description
No. of nodes	193
No. of linear parameters	405
No. of nonlinear parameters	36
Total no. of parameters	441
No. of training data pairs	21
No. of checking data pairs	0
No. of fuzzy rules	81
Optimization tool	hybrid

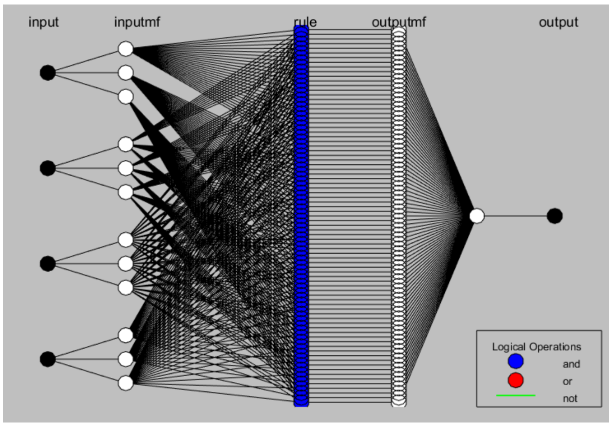


Fig. 8: Neuro-Fuzzy Model Structure.

4. Results and discussion

4.1. Image feature selection

Table 2 shows the values of the extracted features. Pixel count is the sum of all the true pixels in the binary image. The data shown in the RGB, HSV, L*a*b* and YCbCr columns are the mean of each individual components extracted from the masked image.
Feature selection is done to enhance the performance and generalizability of the system to be used like machine learning. Redundant features are being avoided in this type of method because most of the time it contains irrelevant information. It is also useful in data analysis process especially in classification or prediction and close-fitting the relationship of each variable.
Based on the statistical analysis done on the correlations of each image features, the four (4) most relevant parameters to be used are the Y, Cb, Cr and pixel count. The Y, Cb, Cr, and pixel count components has 0.96, 0.90, 0.91 and 0.97 correlation with cultivation period respectively.

Table 2: Extracted Image Features

DAY	Pixel Count	R	G	B	H	S	V	L	A	B	Y	Cb	Cr
20	1193	187.89	197.42	181.93	0.28	0.09	0.77	78.30	-6.05	6.71	17.07	127.97	127.98
20	1180	188.67	196.41	182.49	0.28	0.08	0.77	78.17	-5.17	6.13	17.06	127.97	127.98
20	1170	184.32	192.34	177.95	0.27	0.08	0.75	76.63	-5.38	6.35	17.02	127.97	127.98
25	3190	180.25	194.07	165.31	0.24	0.15	0.76	76.55	-9.89	12.90	18.72	127.82	127.93
25	2927	167.38	176.93	152.41	0.23	0.14	0.69	70.66	-7.78	11.45	18.31	127.85	127.96
25	2968	178.41	191.90	163.68	0.25	0.15	0.75	75.75	-9.70	12.71	18.51	127.84	127.94
30	5259	181.60	196.17	167.23	0.25	0.15	0.77	77.25	-10.19	12.90	20.55	127.71	127.88
30	5049	187.16	200.26	173.50	0.25	0.14	0.79	78.91	-9.26	11.92	20.56	127.73	127.89
30	5195	190.17	201.02	174.33	0.24	0.14	0.79	79.35	-8.43	12.11	20.69	127.72	127.92
35	4963	179.98	192.65	165.64	0.24	0.14	0.76	76.18	-9.21	12.17	20.26	127.73	127.90
35	5285	171.38	182.22	158.70	0.24	0.13	0.71	72.55	-8.04	10.74	20.26	127.76	127.91
35	5039	180.81	197.24	168.67	0.26	0.15	0.77	77.52	-10.76	12.49	20.37	127.73	127.86
40	7114	173.10	187.73	164.18	0.27	0.13	0.74	74.30	-9.37	10.27	21.82	127.70	127.82
40	6905	179.41	190.47	172.14	0.27	0.10	0.75	75.71	-7.16	7.99	21.91	127.76	127.87
40	6959	172.57	184.11	162.04	0.25	0.12	0.72	73.22	-8.03	9.89	21.59	127.71	127.87
45	10198	176.94	194.59	164.70	0.26	0.16	0.76	76.46	-11.45	13.04	24.56	127.44	127.70
45	9497	168.94	181.61	160.48	0.27	0.12	0.71	72.26	-8.30	9.32	23.62	127.63	127.79
45	9621	172.90	189.65	161.51	0.27	0.15	0.74	74.74	-10.89	12.35	23.87	127.50	127.73
50	14367	178.66	197.41	165.38	0.26	0.17	0.77	77.34	-12.17	13.98	28.21	127.15	127.55
50	12974	181.09	199.37	169.59	0.27	0.16	0.78	78.13	-11.62	12.90	27.29	127.29	127.59
50	12965	185.72	202.67	170.80	0.26	0.16	0.80	79.39	-11.46	14.05	27.62	127.20	127.64

4.2. Neuro-fuzzy system

The behavior of the output can easily be predicted using the surface plots. Figure 9 – 11 show all the response of the cultivation period based on two parameters.

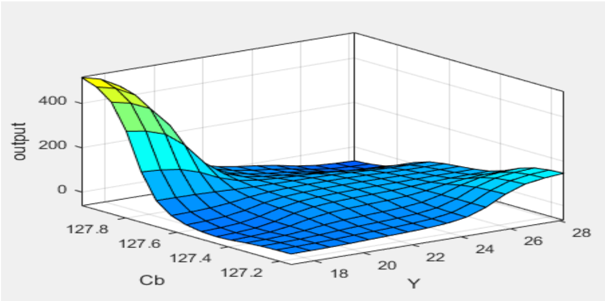


Fig. 9: Surface Plot of Y vs. Cb vs. Cultivation Period.

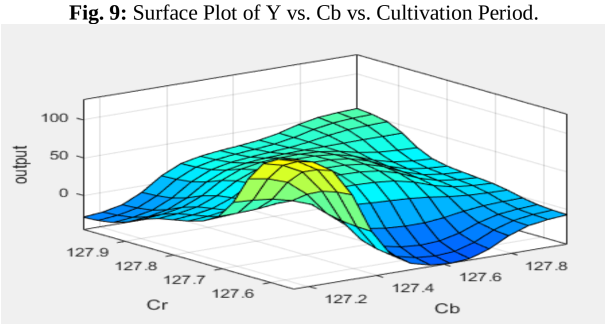


Fig 10: Surface Plot of Cb vs. Cr vs. Cultivation Period

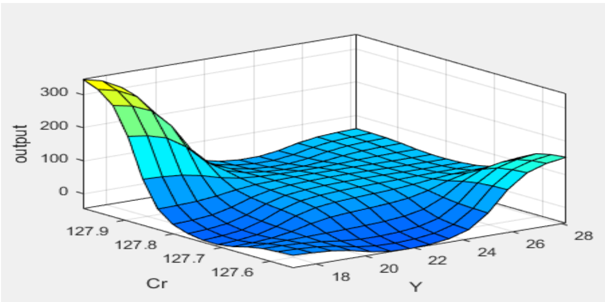


Fig. 11: Surface Plot of Cr vs. Y vs. Cultivation Period.

The relationship of the pixel count and the cultivation period is shown in Figure 12.

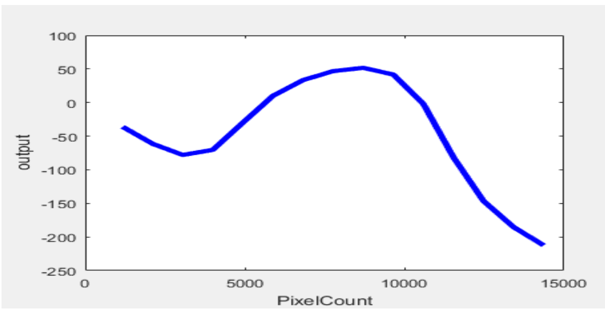


Fig. 12: Surface Plot of Pixel Count vs. Cultivation Period.

The accuracy of the system generated was tested through matching the actual cultivation period and the FIS generated output. Twenty-one (21) test data were used to test the system. The root mean square error (RMSE) value for the neuro-fuzzy model was found to be 0.038868. Index represents the sample number. It can be seen that the FIS data have high fitness to the training data as shown in Figure 13.

Fig. 13: Test Plot.

5. Conclusion

Lettuce cultivation period is one of the most important part of the farming system. It depicts whether the expected yield will be obtained or not. In this study, an image processing technique was used to extract the needed color features in determining the cultivation period. A feature selection algorithm was utilized to define the appropriate color space to be used and resulted to YCbCr selection. The selected features are then modelled using the neuro-fuzzy approach to produce the lettuce cultivation period model. Based on the data obtained, the system was successful for having an accuracy of 99.96%.

6. Recommendations

This study can further be improved with the use of the most advanced image processing techniques and other machine learning algorithm.

Acknowledgement

The authors would like to thank the Intelligent Systems Laboratory (ISL) of the De La Salle University (DLSU) for allowing the researchers to use the Smart Farm in the implementation of this project. Also, the authors would like to express their gratitude to the financial support given by the USAID-STRIDE for this study.

References

[1] W. Xu, H. Jiang and J. Huang, "Regional Crop Yield Assessment by Combination of a Crop Growth Model and Phenology Information Derived from MODIS. Sensor Letters," 2011. https://doi.org/10.1166/sl.2011.1388.

[2] H. M. Rawson and H. G. Macpherson, "IRRIGATED WHEAT," 2000. [Online]. Available: Section 3: Assessing and measuring your crop.

[3] N. R. Canada, "Crop Monitoring & Damage Assessment," 25 11 2015. [Online]. Available: http://www.nrcan.gc.ca/node/14652.

[4] M. Y. Reynolds, "Estimation crop yields and production by integrating the FAO Crop Speci. C Water Balance model with real-time satellite data and ground-based ancillary data," vol. 21, no. 18, pp. 3487-3508, 2000.

[5] S. Shafian and D. Valadanzouj, "Assessment crop yield estimation methods by using satellite imagery," 11 11 2009. [Online]. Available: https://www.geospatialworld.net/article/assessment-crop-yield-estimation-methods-by-using-satellite-imagery/.

[6] L. N. Smith, W. Zhang, M. F. Hansen, I. J. Hales and M. L. Smith, "Innovative 3D and 2D machine vision methods for analysis of plants and crops in the," Computers in Industry, 2018. https://doi.org/10.1016/j.compind.2018.02.002.

[7] S. Sabzi, Y. Abbaspour-Gilandeh and H. Javadikia, "Machine vision system for the automatic segmentation of plants under different lighting conditions," Biosystems Engineering, 2017. https://doi.org/10.1016/j.biosystemseng.2017.06.021.

[8] R. Urena, F. Rodrı´guez and M. Berenguel, "A machine vision system for seeds germination," Computers and Electronics in Agriculture, vol. 32, p. 1–20, 2001. https://doi.org/10.1016/S0168-1699(01)00150-8.
[9] "Merriam-Webster," [Online]. Available: https://www.merriam-webster.com/dictionary/lettuce.
[10] University of Illinois Extension, [Online]. Available: https://extension.illinois.edu/veggies/lettuce.cfm.
[11] VeggieHarvest, "Lettuce Growing and Harvest Information," [Online]. Available: http://veggieharvest.com/vegetables/lettuce.html.
[12] M. H. Kim, E. G. Choi, G. Y. Baek, C. H. Kim, B. O. Jink, B. E. Moon, D. E. Kim and H. T. Kim, "Lettuce growth prediction in plant factory," 2013.
[13] W.-T. Chen, Y.-H. F. Yeh and T.-T. L. Ting-Yu Liu, "An Automatic Plant Growth Measurement System for Plant Factory," 2013.
[14] "Poynton's Color FAQ," 27 February 1997. [Online]. Available: http://homepages.inf.ed.ac.uk/rbf/CVonline/LOCAL_COPIES/POYNTON1/ColorFAQ.html.
[15] Orillo, J.W., Amado, T.M., Arago, N.M. and Fernandez, E., 2016. Rice Plant Disease Identification And Detection Technology Through Classification Of Microorganisms Using Fuzzy Neural Network. Jurnal Teknologi, 78(5-8), pp.25-31 https://doi.org/10.11113/jt.v78.8746.
[16] Orillo, J.W., Cruz, J.D., Agapito, L., Satimbre, P.J. and Valenzuela, I., 2014, November. Identification of diseases in rice plant (oryza sativa) using back propagation Artificial Neural Network. In Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), 2014 International Conference on (pp. 1-6). IEEE.
[17] Valenzuela, I., Amado, T. and Orillo, J.W., 2016. Urine Test Strip Analysis Using Image Processing For Mobile Application. Jurnal Teknologi, 78(5-7), p.2016. https://doi.org/10.11113/jt.v78.8720.
[18] Valenzuela, I.C., Puno, J.C.V., Bandala, A.A., Baldovino, R.G., de Luna, R.G., De Ocampo, A.L., Cuello, J. and Dadios, E.P., 2017, December. Quality assessment of lettuce using artificial neural network. In Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), 2017 IEEE 9th International Conference on (pp. 1-5). IEEE. https://doi.org/10.1109/HNICEM.2017.8269506