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Vision-Based Chlorophyll-a Measurement for Iceberg Lettuce Using Levenberg-Marquardt-Optimized Shallow Neural Network

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***Abstract*—Artificial Neural Networks (ANNs) are increasingly recognized as valuable tools for crop quality parameter measurement. This study investigates the ANNs effectiveness in the predictive measurement of the Chlorophyll-a levels of iceberg lettuce (*Lactuca sativa var. capitata*). This involved using ANNs to link the dataset of extracted RGB and HSV values with the Chlorophyll-a levels retrieved with UV-VIS spectroscopy. For the prediction model, the RGB and HSV values were used as the 6 input predictor values, while the Chlorophyll-a level was used as the 1 output response value. The ANNs were trained on this dataset using the Levenberg-Marquardt algorithm, where the training data comprised 70% of the dataset, the validation data 20% of the dataset, and the test data 10% of the dataset with a layer size of 15. The ANN model demonstrated a strong correlation between the predicted and target outputs, with an accuracy of 98.02% for the test data. This suggests that ANNs can be employed for an accurate and non-invasive monitoring of parameters in iceberg lettuce. The findings also open possibilities for other crops in the Philippines' agricultural industry.**

Keywords—lettuce, digital agriculture, post-harvest, artificial neural networks, machine learning, computer vision

I. Introduction

Agriculture 4.0 aims to revolutionize agricultural productivity by employing technologies like Precision Agriculture, the Internet of Things, Unmanned Aerial Vehicles, the Internet of Underground Things, and others [1]. Computer vision (CV) and Artificial Intelligence (AI) are trending technologies that utilize big data for real-time training of smart machines and predictive models, making agriculture more efficient [2]. Agriculture plays a vital role in the Philippine economy, accounting for approximately 37% of the country's employment [3]. It contributes around 8.6% of the Philippine's gross domestic product (GDP) [4]. The current need for high-quality food has steadily risen in recent decades, especially during the global Covid-19 pandemic [5], driven by factors such as increasing consumer expectations, health consciousness, and environmental awareness. This growing interest has prompted market pressure and a need for comprehensive responses to address consumer demands and concerns [6].

This paper focuses on using vision-based techniques to evaluate Chlorophyll-a levels of Iceberg Lettuce (*Lactuca sativa var. capitata*) using Artificial Neural Networks (ANNs). Lettuce provides numerous health benefits with its low-calorie content, rich nutrient profile, and antioxidants. It supports cardiovascular health, aids in digestion, assists in weight management, and promotes overall well-being [7]. It contains a significant amount of provitamin A compound, beta-carotene, making it an excellent source of vitamin A (21% DV) and vitamin K (97% DV) [8]. Chlorophyll-a levels of the iceberg lettuce will be measured since it offers valuable information about its photosynthetic activity and overall well-being. A greater concentration of Chlorophyll-a in a healthy plant signifies a more efficient photosynthesis process, resulting in improved crop quality, growth, and yield [9]. Therefore, optimizing pre-harvest factors such as Chlorophyll-a can promote quality of agriculture food production [10].

Computer vision (CV) plays a vital role in automating agricultural tasks and postharvest processes. It enables automation and information acquisition for activities like planting, cultivation, farm management, disease control, weed control, robotic harvesting, quality control, damage detection, objective evaluation, fruit and vegetable classification, and composition analysis. CV drives the modernization of the agri-food industry in the era of Industry 4.0 [11]. This study utilized computer vision to extract the RGB and HSV color spaces from the sample lettuce images.

ANNs comprise interconnected nodes that carry out basic processing tasks. Shown in Fig. 1, these are generally organized into layers: there is an input layer, then one or more layers that is hidden, and lastly an output layer. The output layer generates the final prediction of the network, while the hidden layers learn and represent intricate features derived from the input layers [12]. In agriculture, ANNs are increasingly employed by food producers in predicting production outcomes based on multiple variables, identifying diseases and pests, implementing intelligent weed control, and classifying the quality of harvested crops [13]. In this study, ANNs were used to correlate the RGB and HSV color space readings with the extracted Chlorophyll-a values.

This study utilized UV-VIS spectroscopy to accurately determine the Chlorophyll-a values of 18 lettuce specimens. Additionally, the lettuce specimens were photographed and augmented to have a large image dataset. The visual characteristics were then extracted by obtaining the RGB and HSV features from each image in the dataset. The values obtained were then subjected to data fitting using the Neural Net Fitting application in MATLAB. The goal is to establish a connection between the input predictor data (RGB and HSV) and the output response data (UV-VIS spectroscopy-extracted Chlorophyll-a).

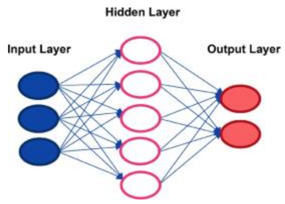


Fig. 1. Visual Depiction for Shallow Artificial Neural Networks [14]

This study contributes to the following:

(1) Development of technology in smart agriculture: this study uses the concepts of ANN and computer vision to advance the field of smart agriculture.
(2) Application of ANN in smart agriculture: this study applies ANN to establish a relationship between visual features (RGB and HSV) extracted from lettuce images and Chlorophyll-a content.
(3) Application of Computer Vision in smart agriculture: this study showcases the use of computer vision techniques to extract RGB and HSV features from lettuce images.

II. Review on Related Literature

A. Computer Vision

In a study conducted on the inventorying and quality assessment of shallots, computer vision and machine learning techniques were employed for crop monitoring and management. The study utilized drones and cameras to monitor health, growth, and yield. It successfully classified the shallots into three size categories (small, medium, and large) using the implemented software. However, the system's performance faced challenges due to inconsistent lighting conditions and the occasional occlusion of vegetables [15].

In the context of plant chlorophyll concentration estimation, a study was conducted on the utilization of RGB extraction techniques. The researchers employed a smartphone camera to capture plant images, subsequently employing image processing software to extract the RGB values from these images. These values were further utilized in conjunction with a regression model to quantify the chlorophyll concentration in the plants. The study's findings highlight the efficacy and cost-effectiveness of the RGB extraction technique as a reliable approach for measuring chlorophyll concentration in plants [16].

Another study conducted on the estimation of chlorophyll concentration in plants utilizes the HSV color space. In this study, plant leaves were captured using a smartphone camera, followed by the conversion of the images from the RGB color space to the HSV color space. Through the application of a thresholding technique, the pixels corresponding to the leaf area were isolated, enabling the calculation of the mean hue and saturation values. These extracted values were subsequently utilized in a regression model to estimate the chlorophyll concentration in the plants. The study demonstrates the effectiveness of the HSV-based method in accurately estimating chlorophyll concentration, presenting potential implications for non-destructive plant health monitoring [17].

Overall, these studies have demonstrated the application of computer vision and machine learning techniques in addressing various agricultural challenges. These highlight the significance of computer vision and image processing in enhancing agricultural practices and providing valuable insights for sustainable crop production.

B. Neural Networks

Neural networks (NNs) have emerged as a powerful tool for image analysis in various agricultural domains. A study centered around the identification of Aspergillus fungi employed microscopic-scale imagery and conducted an analysis utilizing neural networks to classify the various species of fungus. It demonstrates the potential utilization of machine learning techniques in examining extracted data [18]. In a related study, macroscopic images were utilized and analyzed through convolutional neural networks (CNNs). The authors captured imagery of fungal colonies that were cultivated on culture plates and subsequently trained the CNNs to classify the species based on distinctive features observed within the images [19].

Another study conducted on the classification of strawberry quality based on images utilized CNNs. The researchers curated a dataset comprising strawberry images categorized into three distinct quality grades: good, average, and bad. Preprocessing techniques were applied to the images before training the CNN model, which was subsequently employed to classify the strawberries into their respective quality grades. Evaluation of the CNN model's performance demonstrated a remarkable accuracy of over 90% in classifying the strawberries [20]. A similar study analyzed mangoes using the same CNN-based approach that demonstrated an exceptional rate of over 95% in accurately classifying the mangoes [21]. Meanwhile, in a study conducted on lettuce, researchers aimed to predict chlorophyll-b concentration using machine learning algorithms. They utilized 107 lettuce images, extracted leaf features, and optimized a recurrent neural network model called PIGMENTnet. PIGMENTnet outperformed the unoptimized model, providing accurate predictions for lettuce chlorophyll-b concentration [22].

These findings highlight the significant contributions of CNN-based machine learning techniques in advancing agricultural practices, particularly in fungal analysis and fruit quality assessment.

III. Methodology

The study flowchart of this study is presented in Fig. 2. The study aims to develop a vision-based post-harvest system that evaluates the Chlorophyll-a level of an iceberg lettuce sample by using ANN. The developed system will be tested for its accuracy using a regression plot.

Fig. 2. Process Flowchart

The core idea of this study is to use ANNs to associate the dataset of extracted RGB and HSV values with the UV-VIS spectroscopy extracted Chlorophyll-a levels. The chosen software for this study is Matrix Laboratory (MATLAB). Table 1 presents the comprehensive compilation of libraries employed in the study.

TABLE 1. TOOLBOX USED IN MATLAB

Computer Vision Toolbox	Algorithms used to create the color extraction system.
Deep Learning Toolbox	Algorithms used in neural networks.
Statistics and Machine Learning Toolbox	Algorithms used to process data for data fitting.

A. *Data Acquisition*

For this study, Chlorophyll-a data was collected from a group of 18 iceberg lettuces. These lettuce samples underwent UV-VIS Spectroscopy testing to determine their Chlorophyll-a concentrations. UV-VIS spectroscopy involves the measurement of the absorption and transmission of ultraviolet (UV) and visible (VIS) light by a sample. It is a widely used analytical method that provides valuable insights into a given substance's chemical composition and properties [23]. The Chlorophyll-a values obtained through UV-VIS spectroscopy are presented in Table 2. The values were saved in an Excel spreadsheet to serve as the output dataset.

TABLE 2. CHLOROPHYLL-A VALUES

Lettuce Sample Number	Chlorophyll-a (µg/ml)
1	32.83
2	28.89
3	6.7
4	14.73
5	17.17
6	19.92
7	9.11
8	21.6
9	27.95
10	22.69
11	20.37
12	14.94
13	33.82
14	32.36
15	21.09
16	17.15
17	29.72
18	23.44

Regarding the image data, each sample was photographed using a smartphone camera. A total of 18 images were obtained and will serve as the dataset for this study (sample image in Fig. 3). Given the limited number of images collected, a technique called data augmentation will be employed and elaborated upon in the subsequent section.

Fig. 3. Sample image of the Iceberg Lettuce

B. *Data Augmentation*

Data augmentation plays a crucial role in enhancing the performance of machine learning models, particularly in image classification tasks. It involves the generation of new samples that bear similarities to the existing training set. Various image transformation methods are commonly utilized for data augmentation. These include flipping, which horizontally mirrors the image; rotation, which rotates the image at random angles; cropping, which extracts a specific portion of the original image and resizing it if required; and scaling, which resizes the image while preserving its aspect ratio [24].

The dataset augmentation process involved performing the image transformation methods on the 18 original lettuce images. The rotation operation was carried out at various angles, ranging from 0 to 315 degrees in steps of 45 degrees. The cropping operation removed 276 pixels along the width and 176 pixels along the height dimension. A scaling factor of 0.5% was applied to scale the original images. Additionally, the images were flipped horizontally along the vertical axis. The implementation of these augmentation methods resulted in an expanded dataset of 324 images. Shown in Fig. 4 is the implementation of the data augmentation techniques on a sample Iceberg Lettuce image.

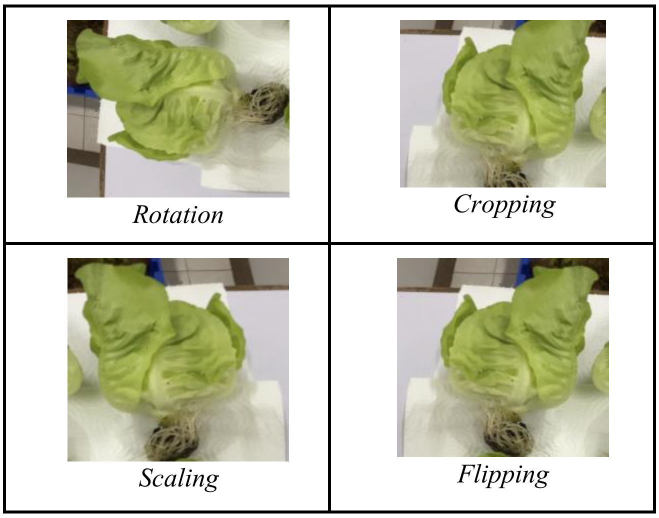


Fig. 4. Implementation of data augmentation techniques on the sample image.

C. *Color Space Spectrum Analysis*

The augmented image data was organized in a systematic manner within a dedicated directory to enable the extraction of RGB and HSV levels. MATLAB was employed as the software tool for extracting the color space information. The read function was utilized to load the image files, and subsequently, the red, green, and blue channels were accessed by referencing the third dimension of the image matrix. To be specific, the red channel could be obtained using image(:, :, 1), the green channel using image(:, :, 2), and the blue channel using image(:, :, 3). After extracting the color channels, the mean or median value was computed for each channel to obtain a single representative value. These values were employed to characterize the overall color of the image. In the case of HSV values, the rgb2hsv function was employed to derive the hue, saturation, and value components based on the HSV color model. Figs. 5 and 6 depict the extracted RGB and HSV readings from the augmented images, respectively.

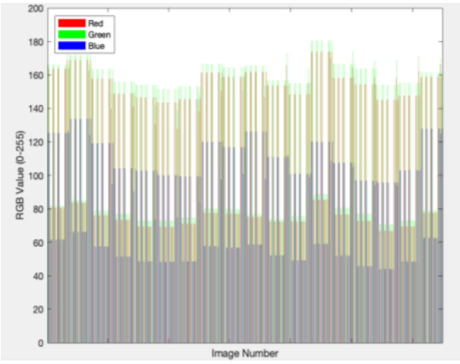


Fig. 5. Extracted RGB readings

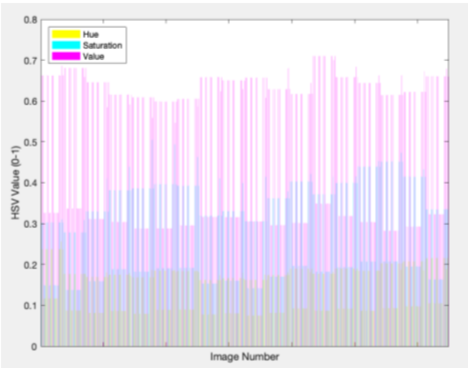


Fig. 6. Extracted HSV readings

The extracted values obtained from the augmented dataset for each original sample were arranged and placed in an Excel spreadsheet. Serving as the input dataset for further analysis and interpretation.

D. *Artificial Neural Network*

Artificial Neural Networks (ANNs) is a type of method in machine learning that are somehow connected to biological neural networks indirectly. ANNs consists of algorithms enabling them to have strong pattern recognition abilities [25]. In this study, there are 6 input predictors, the R, G, B, H, S, and V values, and 1 output response, the Chlorophyll-a level. The ANNs Architecture model of the prediction system is shown in Fig. 7.

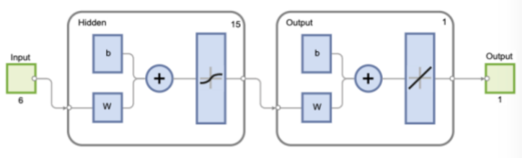


Fig. 7. Artificial Neural Networks Architecture of the Prediction System

The training parameters in the study are shown in Table 3 below. The training data comprises 70% of the dataset, the validation data contains 20% of the dataset, and the test data holds 10% of the dataset. The layer size is set at 15. Upon configuring the parameters, the program was run and started the data fitting. The training algorithm utilized by the Neural Net Fitting App is the Levenberg-Marquardt algorithm (LM), which is one of the fast backpropagations (BP) for optimization. This algorithm is highly recommended as the supervised approach for updating weights and biases in neural networks [26].

TABLE 3. TRAINING PARAMETERS

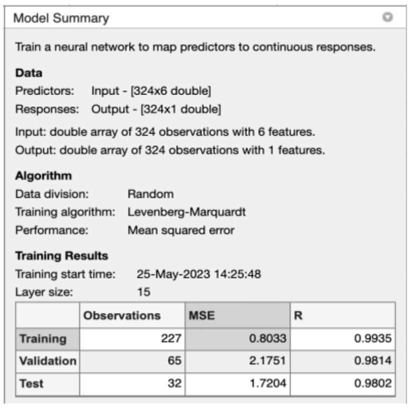
Parameter	Configuration
Training Algorithm	LM Algorithm
Training Data	70%
Validation Data	20%
Test Data	10%
Layer Size	15

IV. RESULTS AND DISCUSSION

Table 4 shows the model summary and training results of the data fitting using the Neural Net Fitting app in MATLAB. The total number of observations is 324, with 227 (70%) placed into training, 65 (20%) into validation, and 32 (10%) into testing. The MSE stands for Mean Squared Error and is an indicator of how close the predicted values are to the regression line. A low value (close to zero) for MSE is preferred. The R represents the accuracy of the model, which shows an accuracy of 96.82%, 90.37%, and 96.12% for the training, validation, and testing, respectively. This implies that the model is accurate in predicting the Chlorophyll-a value based on RGB and HSV values.

The training state plot as shown in Fig. 8, is a graphical representation of the training progress during the fitting of a neural network. An epoch represents a complete cycle through the dataset during the training process. The gradient denotes the vector of the steepest ascent or descent in the optimized function, which had a value of 3.9055 at epoch 62. This indicates a rapid change in the loss function during that cycle, prompting the adjustment of model parameters in response to the gradient. Next, "mu" denotes the learning rate coefficient. In the results, mu was 0.01 at epoch 62. A low learning rate like 0.01 implies cautious and gradual adjustments to ensure stability and prevent overshooting the optimal solution. Lastly, the validation checks indicate the number of times the validation data was evaluated during the training process up to that epoch. In this case, there was a validation check 6 at epoch 62.

TABLE 4. MODEL SUMMARY AND TRAINING RESULTS



Model Summary

Train a neural network to map predictors to continuous responses.

Data

Predictors: Input - [324x6 double]

Responses: Output - [324x1 double]

Input: double array of 324 observations with 6 features.

Output: double array of 324 observations with 1 features.

Algorithm

Data division: Random

Training algorithm: Levenberg-Marquardt

Performance: Mean squared error

Training Results

Training start time: 25-May-2023 14:25:48

Layer size: 15

	Observations	MSE	R
Training	227	0.8033	0.9935
Validation	65	2.1751	0.9814
Test	32	1.7204	0.9802

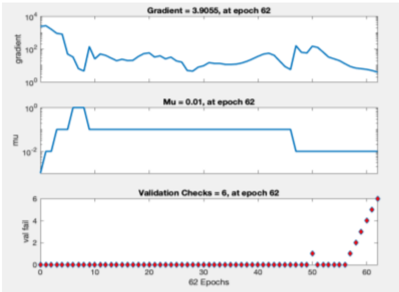


Fig. 8. Training State Plot

The performance plot as shown in Fig. 9, is a graphical representation of the performance of a trained neural network model on both the training and validation data. It illustrates the effectiveness of the neural network model and identifies potential issues such as overfitting or underfitting. In this case, the best validation performance for the model is 2.1751 at epoch 56. This meant that the model, at epoch 56, achieved its highest validation performance.

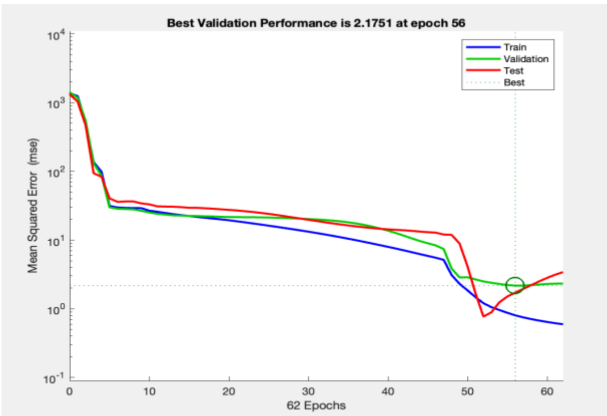


Fig. 9. Performance Plot

The error histogram plot as shown in Fig. 9, provides a visual representation of the distribution of errors or residuals between the predicted outputs of the trained neural network and the corresponding target outputs. In this study, the training had the least amount of error, followed by validation, then finally, the testing.

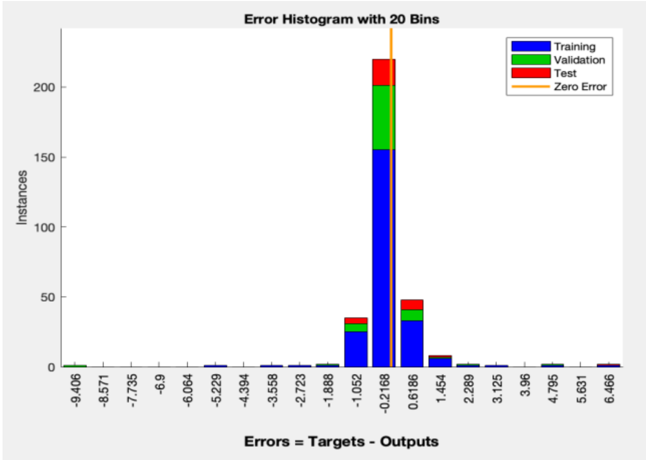


Fig. 10. Error Histogram Plot

The regression plot depicted in Fig. 10 illustrates the association between the predicted outputs generated by a neural network model that has undergone training, and the corresponding target outputs within a regression context. The presented plots exhibit a substantial R-value of 0.98 or higher for the training, validation, and testing. This indicates a strong correlation between the predictor inputs and response outputs. Furthermore, the regression line encapsulates a considerable number of the data points, signifying the model's accuracy in predicting Chlorophyll-a values using the extracted RGB and HSV readings. However, it is notable to mention the presence of outliers within the system. These models can be improved by integrating evolutionary computing and advanced imaging techniques [27-29].

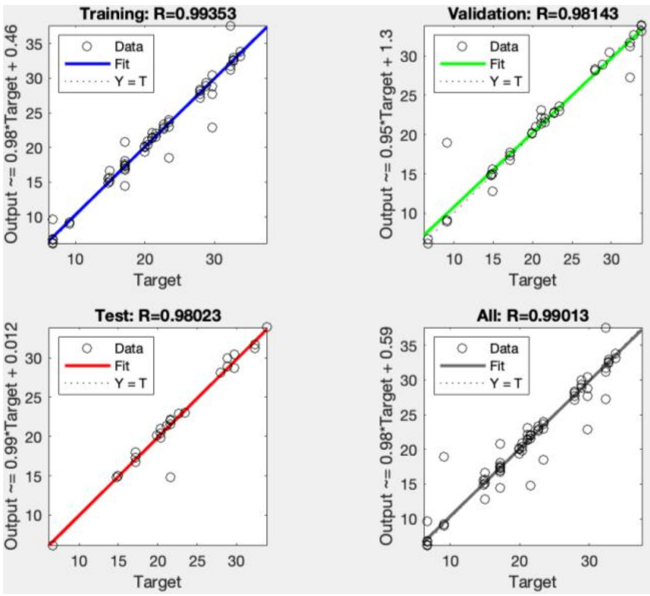


Fig. 11. Regression Plot

V. CONCLUSION

This study effectively established a correlation between input predictor data comprising RGB and HSV extracted values and output response data derived from UV-VIS spectroscopy measurements of Chlorophyll-a levels. By employing ANNs and leveraging the Neural Net Fitting App in MATLAB, a predictive model was successfully developed to estimate the Chlorophyll-a level in Iceberg lettuce based on its RGB and HSV color signatures. These findings provide compelling evidence for the feasibility of utilizing the RGB and HSV color spaces in employing an ANN-backed vision-based system to assess the Chlorophyll-a level in Iceberg lettuce samples. The integration of computer vision techniques and ANNs presents a promising approach in the context of a non-invasive Chlorophyll-a evaluation in Iceberg lettuce. Further research and development of the system could lead to potential applications in vision-based post-harvest applications of various crops.

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REFERENCES

[1] H. C. Pacco, "Simulation of temperature control and irrigation time in the production of tulips using Fuzzy logic," *Procedia Computer Science*, vol. 200, pp. 1-12, 2022.

[2] A. Subeesh and C. Mehta, "Automation and digitization of agriculture using artificial intelligence and internet of things," *Artificial Intelligence in Agriculture*, vol. 5, pp. 278-291, 2021.

[3] C. Habito and R. Briones, "Philippine Agriculture over the Years: Performance, Policies and Pitfalls", *Policies to Strengthen Productivity in the Philippines*, 2005.

[4] L. Mopera, "Food Loss in the Food Value Chain: The Philippine Agriculture Scenario," *Journal of Developments in Sustainable Agriculture*, pp. 8-16, 2016.

[5] N.C. Aksoy, E.T. Kabadayi, and A.K. Alan, "An unintended consequence of Covid-19: Healthy nutrition," *Appetite*, vol. 166, 2021.

[6] D.C. Petrescu, I. Vermeir, and R.M. Petrescu-Mag, "Consumer Understanding of Food Quality, Healthiness, and Environmental Impact: A Cross-National Perspective," *Int J Environ Res Public Health*, vol. 17, no. 1, p. 169, 2019.

[7] M. J. Kim, Y. Moon, J. C. Tou, B. Mou, and N. L. Waterland, "Nutritional value, bioactive compounds and health benefits of lettuce (Lactuca sativa L.)," *Journal of Food Composition and Analysis*, vol. 49, pp. 19-34, 2016.

[8] R. Das and C. Bhattacharjee, "Lettuce. Nutritional Composition and Antioxidant Properties of Fruits and Vegetables," in Nutritional Composition and Antioxidant Properties of Fruits and Vegetables, pp. 143-157, 2020.

[9] U.S. Environmental Protection Agency, "Chlorophyll content". Available: https://www.epa.gov/national-aquatic-resource-surveys/indicators-chlorophyll.

[10] R. Concepcion II, E. Dadios, A. Bandala, J. Cuello and Y. Kodama, "Hybrid Genetic Programming and Multiverse-based Optimization of Pre-Harvest Growth Factors of Aquaponic Lettuce Based on Chlorophyll Concentration," *International Journal on Advanced Science, Engineering and Information Technology*, vol. 11, no. 6, pp. 2128-2138, 2021.

[11] J. A. Fracarolli, F. F. A. Pavarin, W. Castro, and J. Blasco, "Computer vision applied to food and agricultural products," *in Proc. Revista Ciência Agronômica*, vol. 51, 2020.

[12] Y. H. Liu, "Feature extraction and image recognition with convolutional neural networks," *in Journal of Physics: Conference Series*, vol. 1087, no. 6, 2018.

[13] S. Kujawa and G. Niedbała, "Artificial Neural Networks in Agriculture," *Agriculture*, vol. 11, no. 6, pp. 497, 2021. doi: 10.3390/agriculture11060497.

[14] H. Elwahsh, E. El-Shafeiy, S. Alanazi, and M. Tawfeek, "A new smart healthcare framework for real-time heart disease detection based on deep and machine learning," *PeerJ Computer Science*, vol. 7, 2021.

[15] A. A. Boatswain Jacques, V. I. Adamchuk, J. Park, G. Cloutier, J. J. Clark, and C. Miller, "Towards a machine vision-based yield monitor for the counting and quality mapping of shallots," *Frontiers*, vol. 8, p. 62706.

[16] Y. Liang, D. Urano, K.L. Liao, et al., "A nondestructive method to estimate the chlorophyll content of Arabidopsis seedlings," *Plant Methods*, vol. 13, p. 26, 2017.

[17] M. Mahmoodi-Eshkaftaki, J. Khazaei, and K. Vahdati, "Chlorophyll Content Estimation Using Image Processing Technique," *Journal of World Applied Sciences*, 2013.

[18] R. K. C. Billones, E. J. Calilung, E. P. Dadios and N. Santiago, "Aspergillus Species Fungi Identification Using Microscopic Scale Images," *2020 IEEE 12th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM)*, Manila, Philippines, pp. 1-5, 2020.

[19] R. K. C. Billones, E. J. Calilung, E. P. Dadios and N. Santiago, "Image-Based Macroscopic Classification of Aspergillus Fungi Species Using Convolutional Neural Networks," *2020 IEEE 12th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM)*, pp. 1-4, 2020.

[20] L. A. Acero, J. D. S. Ong, C. J. L. Shi, E. P. Dadios and R. K. C. Billones, "Strawberry Quality Classification Utilizing Convolutional Neural Network," *2021 IEEE 13th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM)*, pp. 1-4, 2020.

[21] J. C. V. Puno, R. K. D. Billones, A. A. Bandala, E. P. Dadios, E. J. Calilune and A. C. Joaquin, "Quality Assessment of Mangoes using Convolutional Neural Network," *2019 IEEE International Conference on Cybernetics and Intelligent Systems (CIS) and IEEE Conference on Robotics, Automation and Mechatronics (RAM)*, pp. 491-495, 2019.

[22] H. L. Aquino, R. S. Concepcion, R. R. Vicerra, C. H. Mendigoria, O. J. Alajas, E. P. Dadios and J. Cuello, "PIGMENTnet: Chlorophyll-b Prediction of Lactuca Sativa Leaf Under Hybrid Genetic Algorithm and Recurrent Neural Network," *2021 IEEE Region 10 Conference (TENCON)*, pp. 248-253, 2021.

[23] JoVE Science Education Database, "Analytical Chemistry. Ultraviolet-Visible (UV-Vis) Spectroscopy," *JoVE*, 2023.

[24] J. Shijie, W. Ping, J. Peiyi, and H. Siping, "Research on data augmentation for image classification based on convolution neural networks," *2017 Chinese Automation Congress (CAC)*, pp. 4165-4170, 2017.

[25] Hosameldin Ahmed; Asoke K. Nandi, "Artificial Neural Networks (ANNs)," in Condition Monitoring with Vibration Signals: Compressive Sampling and Learning Algorithms for Rotating Machines, IEEE, 2019, pp.239-258, doi: 10.1002/9781119544678.ch12.

[26] Vesali, F., Omid, M., Kaleita, A., and Mobli, H., "Development of an Android app to estimate chlorophyll content of corn leaves based on contact imaging," Computers and Electronics in Agriculture, vol. 116, pp. 211-220, 2015.

[27] R. S. Concepcion, E. P. Dadios and J. Cuello, "Non-destructive in situ measurement of aquaponic lettuce leaf photosynthetic pigments and nutrient concentration using hybrid genetic programming," *AGRIVITA Journal of Agricultural Science*, vol. 43, no. 3, pp. 589-610, 2021.

[28] R. S. Concepcion and E. P. Dadios, "Bioinspired optimization of germination nutrients based on Lactuca sativa seedling root traits as influenced by seed stratification, fortification and light spectrums," *AGRIVITA Journal of Agricultural Science*, vol. 43, no. 1, pp. 174-189, 2021.

[29] S. K. Singh, V. Hoyos-Villegas, J. D. Ray, J. R. Smith and F. B. Fritschi, "Quantification of leaf pigments in soybean (Glycine max (L.) Merr.) based on wavelet decomposition of hyperspectral features," *Field Crops Research*, vol. 149, pp. 20-32, 2013.