Estimation of Moisture Content in *Solanum Lycopersicum* Leaves Using Color Extraction Algorithm

Miguel Angelo F. del Rosario
School of Electrical, Electronics, and Computer Engineering
Mapúa University
Manila, Philippines
mafdelrosario@mymail.mapua.edu.ph

Hiroshi A. Kanie
School of Electrical, Electronics, and Computer Engineering
Mapúa University
Manila, Philippines
hakanie@mymail.mapua.edu.ph

Jocelyn F. Villaverde
School of Electrical, Electronics, and Computer Engineering
Mapúa University
Manila, Philippines
jfvillaverde@mapua.edu.ph

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***Abstract*—We estimated the moisture content in Tomato (*Solanum Lycopersicum*) leaves by using the Color Extraction Algorithm and the kurtosis value of the leaves from the grayscale histogram. An Estimation Model was developed using linear regression. The hardware comprised a Raspberry Pi 3 Model B, Raspberry Pi Camera Module v1.3, and two buttons. 12 tomato plants were raised for 30 days with different water volumes applied. Leaf images were captured and processed using Python programming. OpenCV and NumPy libraries were used to read the captured image, convert it to grayscale, remove its background, crop white areas, apply a filter, and create its color histogram. The dry-oven method was implemented to calculate the exact moisture content of tomato plant leaves. A paired t-test result showed a p-value of 0.0876 accepting the null hypothesis. Thus, no significant difference between the measured moisture level (dry-oven) and the estimated moisture level of the tomato leaves was observed.**

***Keywords*—color extraction algorithm, image processing moisture content, raspberry pi 3b, tomato plant leaves.**

I. Introduction

One of the most essential elements for all living organisms to survive is water [1]. Plants require the most water. Water allows plants to absorb nutrients, control their temperature, perform photosynthesis, and otherwise function effectively [2]. Plants, on the other hand, require frequent watering. Plants overwatered succumb to suffocation and die. Underwatered plants, on the other hand, progressively perish due to a lack of moisture. Thus, it is necessary to examine the moisture level of the plants to determine whether or not to water them for them to have efficient photosynthesis, which in return keeps the plants healthy and long-lasting.

Measuring the moisture content in plants is essential to sustain the plant. Burkhardt and Gerchau [3] connected the electrical resistance and sensors directly to the plant leaves. The results were compared to the ambient relative humidity. Using spectroscopic and chemometric analyses, Zhang et al. [4] detected the moisture content. According to Zhang, spectroscopic analysis is widely used in agriculture since it can give non-destructive, quick, and precise measurements. VIS/NIR spectroscopy is used to determine the moisture content of the plant leaves. Similarly, Sabar et al. [5] used Visual Near-Infrared or hyperspectral image processing. Using hyperspectral imaging, Sabar et al. predicted the moisture content by capturing an image of the dried sea cucumber, enhancing and extracting the image, and applying regression with a non-destructive and fast method. Shivashankar conducted a more straightforward method [6] to determine the moisture content in percentage by measuring the weight of the newly trimmed and oven-dried leaves. The drying process was conducted several times to provide an estimated moisture content. While earlier studies' methodologies proved to be beneficial, there need to be more studies on measuring the moisture content in plants using image processing methods. No study has estimated the moisture content of tomato (Solanum Lycopersicum) leaves using the Color Extraction Algorithm.

The objective of the study was to implement a color extraction algorithm for determining the moisture content in tomato leaves. We implemented a color extraction algorithm to extract the color value of the tomato (*Solanum Lycopersicum*) leaf image. Then, we created an estimation model to estimate moisture content. A paired t-test was used to compare the values from the oven-dry method moisture content and the estimated moisture content.

As the availability of materials in previous studies was not used outside the laboratory, devices to estimate the moisture content in plants were limited. We created a device that did not require laboratory apparatuses. The device can be used with other image-processing algorithms. It benefits citizens, particularly farmers and greenhouse workers, as it is cheaper, readily available, and provides information on moisture of the plant.

II. Literature Review

A. Tomato Plants and Leaves

Tomato crops, scientifically known as *Solanum Lycopersicum*, are prevalent in the Philippines. Altoveros and Borromeo [7] stated that tomatoes are the second most crucial fruit vegetable in the Philippines. 17,700 ha of the land was farmed to produce about 173,700 tons of tomatoes in 2001. This indicated that farmers most likely had tomato crops in their fields. Reference [3] determined the moisture content of plants by connecting the sensors to the plant's leaf. Maintaining the moisture content benefits the plant. Other studies [8, 9] focused on the qualities of the tomato plant with image processing.

B. Moisture Content of Plant Leaves

Reference [10] measured water contents in leaves and concluded that the moisture content level in plants is important in crop management. In addition, the moisture content of plants is used in agriculture, specifically in irrigation, crop fertilizer, and remote sensing [11]. Similar studies [12,13] focused on soil moisture in irrigation systems.

C. Color Extraction Image Processing

Color Histogram Image Processing was used to check the histogram of each color and its RGB values for detecting

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vehicles and weather conditions [14]. It was used to capture the surface of oranges and classify them using biopolymer extraction through its RGB color values [15]. It was also used in detecting diseases on plant leaves [16–18].

D. Raspberry Pi in Image Processing

Raspberry Pi was used to develop a street lighting system with object detection, control the light's dimness, and detect people walking in the streets [19]. Reference [20] used the Raspberry Pi and YOLO Algorithms for food recognition of visually impaired people. In medical applications, Ref. [21] detected and identified abaca plant diseases using a Convolutional Neural Network (CNN) with Raspberry Pi. Moreover, a classification of defective and non-defective ATX power supplies was developed with a non-contact testing method [22]. Reference [23] used Raspberry Pi and IoT to monitor the temperature and humidity of cherry tomato greenhouses.

E. Moisture Content Detection of Tomato Leaves

A hyperspectral image processing technique was used to gather tomato leaves' internal information and external features to detect their moisture content [24]. Reference [25] used image processing to detect the holly leaves' moisture content. By using polarized active imaging technology, it was matched up with the Speeded Up Robust Feature (SURF) algorithm. The drying process was used to measure the actual leaf moisture. Similar processes were used in studies of maize leaves and tomato plant growth [26,27].

III. Methods and Materials

A. Conceptual Framework

Figure 1 shows the IPO conceptual framework. Tomato leaf images in jpg file format were the primary input of the system, which was collected from twelve different tomato plants using a Raspberry Pi camera module. The process was conducted with a leaf color extraction algorithm and an estimation model with kurtosis. First, leaf color was extracted to obtain the mean and kurtosis values of the pixels of the images using the grayscale histogram distribution. The estimation model was created by formulating the linear regression. The equation for the linear regression was obtained from the values of the mean and kurtosis of the training model. The final output of the system was the moisture content of the tomato plant leaves.

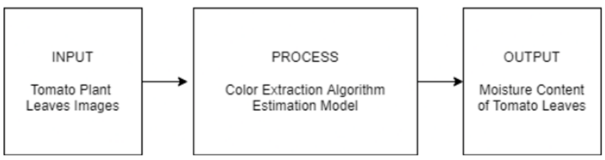

Fig. 1. Conceptual framework.

B. Hardware

Figure 2 shows the project's hardware block diagram. In designing and prototyping the system, we used Raspberry Pi 3 B as the brain of the system for color extraction and estimation. A 5 MP 1-9-p Raspberry Pi Camera Module v1.3 was used to capture images of tomato leaves and served as the image sensor. A push button was added as an indicator to capture an image from the camera module. The power was supplied with a 5V 2.5A micro-USB connector. The estimated moisture level of the leaf was displayed on the 16 × 2 i2c LCD Display, which was connected to the output of the Raspberry Pi.

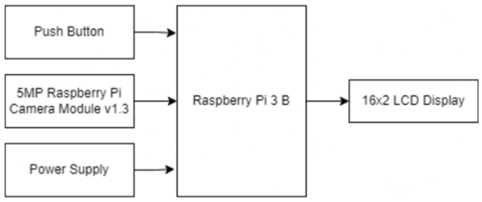

Fig. 2. Hardware setup.

Figure 3 shows the internal view and the prototype (3D view). The case was in the dimensions of 23 × 20 × 20 cm. On the top side, the 16 × 2 i2c LCD Display and the two (2) push buttons were placed for users to see the results and press the buttons. The first button was used to capture the image, while the second button to turn off the Raspberry Pi (RPi) device. The RPi was placed on the top back part to connect to all components. On the top internal side, the Raspberry Pi 5 MP Camera Module v1.3 was placed to take a picture of the tomato plant leaf. Additional LEDs were attached to reduce the noise of the captured image.

Fig. 3. Developed prototype of device.

C. Software Development

Python was used for creating the grayscale histogram and solving the kurtosis estimation model.

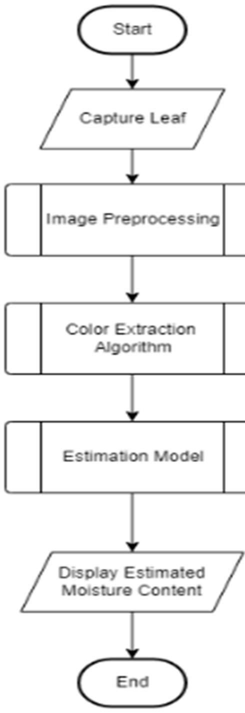

Fig. 4. Flowchart of the Main Program

The program captured an image of the tomato leaf and then processed it with the Image Preprocessing Module and the Color Extraction Algorithm Module. Next, to determine the value of the estimated moisture content, the program ran the Estimation Model of a tomato leaf. Then, the estimated moisture content was displayed on an LCD screen.

The Image Preprocessing module converted the image into a grayscale to extract the image's color information as grayscale features corresponding to the color features of the image. Using the OpenCV library, the image's background was removed by setting its threshold in binary. The resulting image was cropped to center the image and remove unnecessary pixels. Then, linear spatial filtering was applied to the cropped image to remove external noise. Finally, the filtered image was converted to a transparent image that consisted of the pixels of the leaf and disregarded the pixels of the background.

The Color Extraction Algorithm module calculated the value of the grayscale histogram for each number of pixels as the RGB values of the captured image. The mean of the grayscale histogram value was calculated as the average RGB value of the image. Lastly, the program calculated the kurtosis of the grayscale image. The mean and kurtosis were correlated with the leaves' moisture content to predict the leaf moisture level [17]. The concentration of grayscale distribution around the mean of the captured image was obtained as a result. A lower Kurtosis value indicated a more concentrated distribution, while a high value indicates a dispersed distribution. The Estimation Model substituted variables with the Kurtosis value. The values of the variable were taken from the generated equation after training several sample data through Linear Regression. Then, the program simplified and calculated the result using the equation.

D. Experimental Setup

The experiment comprised image collection and direct measurement. Twelve-tomato plant and the camera were used for the image collection. Each leaf image was collected to estimate its moisture content. The leaf was placed on a flat surface on a white background. The camera captured the leaf image from 17 to 19 cm from the leaf. Additional background lights were used for a clear photo of the leaves with reduced noise. The image collected was used for Color Extraction Image Processing, and its estimated value was output on the LCD. For the direct measurement, a dry oven and a weighing scale were used. Each leaf was weighed for fresh weight. The leaves were placed in a dry oven and dried at 80° C for 30 s. After the period, each leaf will again be weighed to collect its dry weight and calculate its measured moisture content.

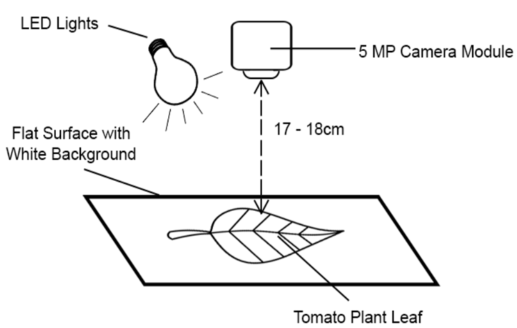

Fig. 5. Experimental setup.

E. Images Collection

Table I shows the distribution of the moisture content of the tomato leaves. Groups A, B, and C included four tomato plant leaves. The amount of water needed for tomato plants is 400 to 600mL per plant for 90 to 120 days [18]. Thus, Group A was watered 600 mL daily, Group B was watered 500 mL every three days, and Group C was watered 400 mL every five days. The duration of plant irrigation was thirty (30) days. This group distribution was decided to ensure different measurements between each group. Group A showed fresh leaves, Group B showed moderately dried leaves, and Group C shoed dried leaves.

TABLE I. TOMATO LEAVES GROUP DISTRIBUTION

Groups	No. of Leaves	Water Given	Frequency
A	4	600mL	Daily
B	4	500mL	Every three days
C	4	400mL	Every five days

RPi 5 MP Camera v1.3 from the RPi 3 Model B was used to capture leaf images of a tomato plant (Solanum Lycopersicum). One leaf was chosen randomly and cut from its stem. 12 leaves were used in the experiment and grouped based on their water volume irrigated. For identification, leaves were grouped and numbered based on irrigated water volume. Group A consisted of leaves L01 to L04; Group B consisted of leaves L05 to L08; Group C consisted of leaves L09 to L12. The image taken with the camera had a resolution of 1600×900 and was saved in a JPG format.

Figures 6 to 8 show the images of tomato plant leaves by their corresponding group and labels. Figure 6 shows a fresh group of leaves from Group A. Figure 7 shows a moderately dry group of leaves from Group B. Figure 8 shows a dry group of leaves from Group C.

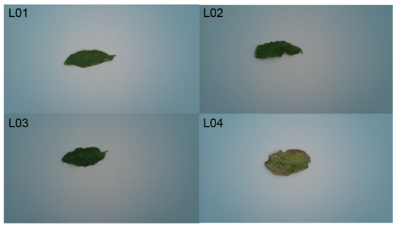

Fig. 6. Captured image from Group A.

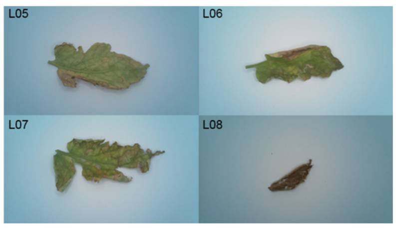

Fig. 7. Captured image from Group B.

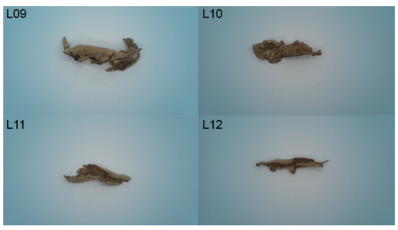

Fig. 8. Captured image from Group C.

F. Dry Oven Method

The dry oven method was used to measure the leaves' moisture content. Each leaf's weight, before and after drying was measured using a 0.001 µg scale. The fresh weight of the leaf in grams was measured and the leaf was dried in an oven. Paper towels were used to wrap the leaves before placing them in the oven. The oven was set to medium heat and turned on for 60 s. After drying, the weight of the lead in grams was calculated.

$$\text{Moisture Content} = \frac{\text{Fresh Weight - Dry Weight}}{\text{Fresh Weight}} \quad (1)$$

With the two weight values, the moisture content was calculated using (1). The moisture content of each leaf in Group A ranged from 70 to 90%, that in Group B ranged from 50 to 70%, and that in Group A was lower than 50%.

G. Kurtosis from Color Extraction Algorithm

To obtain the kurtosis of the image, the Color Extraction Algorithm was used. The RGB image captured was read using the OpenCV library as a converted grayscale image using the imread function. The background of the raw images was removed by using Otsu's threshold method to obtain the grayscale thresholds and remove background noise. This was conducted by transforming the image into a binary image to determine the threshold and center mass of the image. Afterward, it was cropped, and a linear spatial filter was applied using the filter2d command. The grayscale color histogram of the input image was then computed using the NumPy library. The frequency of each intensity level from 0 to 255 was obtained. Using the SciPy library, the kurtosis of the grayscale color histogram was calculated by using the kurtosis command. The histogram showed a peak intensity from 50 to 150 with frequencies ranging from 2000 to 10,000. Samples of the image preprocessing are shown in Fig. 9.

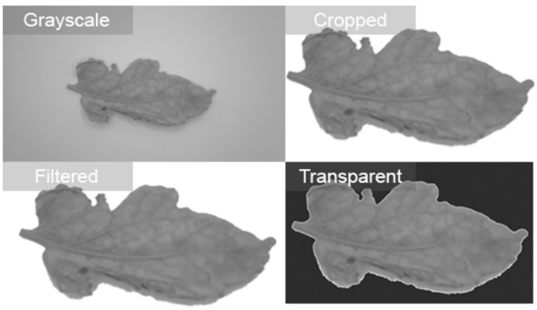

Fig. 9. Sample of Image Pre-processing

Table II displays the kurtosis of each leaf from 1 to 12. The kurtosis values of leaves 1 to 4 (Group A) ranged from 0.5 to 4.7, 5 to 8 (Group B), and 9 to 12 (Group C). The kurtosis varied depending on its color and intensity values.

TABLE II. KURTOSIS VALUE FOR EACH LEAF

Leaf No.	Kurtosis Value
1	3.233110174
2	4.657639904
3	1.233305259
4	3.305558118
5	4.028968928
6	1.788163088
7	2.999564878
8	1.84472408
9	7.709195967
10	6.272700004
11	1.467945156
12	4.157477124

H. Estimation Model

We used a dataset that consisted of the actual moisture content and kurtosis of 90 leaves. A linear regression was used to predict the moisture content of tomato leaves.

$$\text{Moisture Content - } 2.917x + 15.19 \quad (2)$$

where x is the kurtosis obtained from the Color Extraction method. The result of the moisture content equation was displayed on the LCD of the prototype for 10 s. The measured moisture content ranges from 17.00 to 81.00%.

IV. RESULTS AND DISCUSSION

Table III displays the measured moisture content from each leaf's direct and estimated moisture content from 1 to 12.

TABLE III. MEASURED AND ESTIMATED MOISTURE CONTENT OF LEAVES

Leaf No.	Moisture Content from Direct Method	Estimated Moisture Content
1	78.1250	80.4873
2	63.7500	61.6871
3	76.5625	71.1159
4	63.6364	61.7496
5	32.1429	35.7602
6	28.2540	29.2279
7	34.5776	30.6135
8	36.7347	34.8188
9	14.0351	16.7475
10	23.148	26.1204
11	18.2927	19.2827
12	17.9775	18.0068

Table 4 displays the Paired T-Test statistical treatment values. The average difference (d) was 0.13489, the standard deviation (s) was 2.91444, and the t-value was 0.066. The p-value was 0.876. Thus, the null hypothesis was rejected at a significance level of 95%. The oven-dry method and the predicted moisture had significant differences.

V. CONCLUSION AND RECOMMENDATION

We estimated the moisture content in Tomato (Solanum Lycopersicum) leaves by using the Color Extraction Algorithm, the grayscale histogram, and an Estimation Model through linear regression. Kurtosis values of the leaves were used in the estimation. 12 tomato plants were raised for 30 days with different watering volumes and frequencies. Leaf images were captured and processed using OpenCV and NumPy libraries. The images were converted to grayscale to remove their background, crop white areas, apply a filter, and create their color histogram with a filter. The moisture content of leaves ranged from 17.0 to 81.0%. The dry-oven method was used to measure the exact moisture content of tomato plant leaves. The paired T-test resulted in a p-value of 0.876 to reject the null hypothesis. Therefore, there was no significant difference between the measured and estimated moisture content of the tomato leaves. An upgraded camera with autofocus may help capture clearer images at close range, and a smaller casing for the prototype is recommended.

REFERENCES

[1] M. Chaplin "Water: its importance to life. Biochemistry and Molecular Biology Education." 29. 54 - 59. 10.1111/j.1539-3429.2001.tb00070.x. 2001

[2] N. Turner, and G. Burch (1983). The Role of Water In Plants. I. Teare and M. Peet. Crop Water Relations, John Wiley and Sons, New Jersey.

[3] J. Burkhardt, and J. Gerchau. "A new device for the study of water vapour condensation and gaseous deposition to plant surfaces and particle samples." Atmospheric Environment 28.12: 2012-2017. 1994.

[4] Q. Zhang, Q. Li, and G. Zhang. "Rapid determination of leaf water content using VIS/NIR spectroscopy analysis with wavelength selection." Spectroscopy: An International Journal 27.2 pp. 93-105. 2012.

[5] A. Sabar, H. Saputro and C. Imawan, "Moisture Content Prediction System of Dried Sea Cucumber (Beche-de-mer) Based on Visual Near-Infrared Imaging," 2019 6th International Conference on Instrumentation, Control, and Automation (ICA), 2019, pp. 167-171, doi: 10.1109/ICA.2019.8916705.

[6] M. Shivashankar (2015). Study on leaf moisture status of some Mulberry varieties as influenced by Foliar spray of Paras (Mulberry Garden). International Journal of Current Microbiology and Applied Sciences ISSN: 2319-7706 Volume 4, 1200-1206.

[7] N. Altoveros and T. Borromeo (2007). The State of the Plant Genetic Resources for Food and Agriculture of the Philippines (1997-2006). A Country Report. Bureau of Plant Industry and Food and Agriculture Organization of the United Nations, Rome.

[8] J. Legaspi, J. R. Pangilinan and N. Linsangan, "Tomato Ripeness and Size Classification Using Image Processing," 2022 5th International Seminar on Research of Information Technology and Intelligent Systems (ISRITI), Yogyakarta, Indonesia, 2022, pp. 613-618, doi: 10.1109/ISRITI56927.2022.10052810.

[9] M. K. D. Anticuando, C. K. R. Directo and D. A. Padilla, "Electronic Nose and Deep Learning Approach in Identifying Ripe Lycopersicum esculentum L. Tomato Fruit," 2022 13th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kharagpur, India, 2022, pp. 1-6, doi: 10.1109/ICCCNT54827.2022.9984415.

[10] X. Jin, C. Shi, C.Y. Yu, T. Yamada, & E.J. Sacks "Determination of leaf water content by visible and near-infrared spectrometry and multivariate calibration in Miscanthus." Frontiers in plant science 8, pp. 721. 2017.

[11] E.R. Hunt, and B.N. Rock. "Detection of changes in leaf water content using near-and middle-infrared reflectances." Remote sensing of environment vol. 30.1 pp: 43-54. 1989.

[12] M. V. Caya et al., "Capacitance-Based Soil Moisture Sensor for Irrigation Scheduling Application," 2018 3rd International Conference on Computer and Communication Systems (ICCCS), Nagoya, Japan, 2018, pp. 477-481, doi: 10.1109/CCOMS.2018.8463256.

[13] A. N. Yumang, A. C. Paglinawan, L. A. A. Perez, J. F. F. Fidelino and J. B. C. Santos, "Soil infiltration rate as a parameter for soil moisture and temperature based Irrigation System," 2016 6th IEEE International Conference on Control System, Computing and Engineering (ICCSCE), Penang, Malaysia, 2016, pp. 286-291, doi: 10.1109/ICCSCE.2016.7893586.

[14] D. A. Padilla, J. F. Villaverde, J. J. T. Magdaraog, A. J. L. Oconer and J. P. Ranjo, "Vehicle and Weather Detections Using Real Time Image Processing Using Optical Flow and Color Histogram," 2019 5th International Conference on Control, Automation and Robotics (ICCAR), 2019, pp. 880-883, doi: 10.1109/ICCAR.2019.8813346.

[15] C. B. Soriano, D. K. Ferrer, J. F. Villaverde, and D. A. Padilla "Classification of citrus sinensis peel for production of biopolymers using probability distribution function". Paper presented at the 2021 7th International Conference on Control Science and Systems Engineering, ICCSSE 2021, 319-323. doi:10.1109/ICCSSE52761.2021.9545158

[16] A. N. Yumang, J. M. Baguisi, B. R. S. Buenaventura and C. C. Paglinawan, "Detection of Black Sigatoka Disease on Banana Leaves Using ShuffleNet V2 CNN Architecture in Comparison to SVM and KNN Techniques," 2023 15th International Conference on Computer and Automation Engineering (ICCAE), Sydney, Australia, 2023, pp. 281-286, doi: 10.1109/ICCAE56788.2023.10111367.

[17] J. Al Gallenero and J. Villaverde, "Identification of Durian Leaf Disease Using Convolutional Neural Network," 2023 15th International Conference on Computer and Automation Engineering (ICCAE), Sydney, Australia, 2023, pp. 172-177, doi: 10.1109/ICCAE56788.2023.10111159.

[18] N. C. Ibarra, M. P. Rivera and C. O. Manlises, "Determination of Leaf Degradation Percentage for Banana leaves with Panama Disease Using Image Segmentation of Color Spaces and OpenCV," 2023 15th International Conference on Computer and Automation Engineering (ICCAE), Sydney, Australia, 2023, pp. 269-275, doi: 10.1109/ICCAE56788.2023.10111455.

[19] J.A. Galindo and & M. V. Caya "Development of street lighting system with object detection" 2018 IEEE 10th International Conference on Humanoid, Nanotechnology, Information Technology, Communication, and Control, Environment and Management, HNICEM 2018, doi:10.1109/HNICEM.2018.8666410

[20] A. N. Yumang, D. E. S. Banguilan, and C. K. S. Veneracion, "Raspberry PI based Food Recognition for Visually Impaired using YOLO Algorithm," 2021 5th International Conference on Communication and Information Systems (ICCIS), 2021, pp. 165-169, doi: 10.1109/ICCIS53528.2021.9645981.

[21] L. T. Buenconsejo and N. B. Linsangan, "Classification of Healthy and Unhealthy Abaca leaf using a Convolutional Neural Network (CNN)," 2021 IEEE 13th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM), 2021, pp. 1-5, doi: 10.1109/HNICEM54116.2021.9732050.

[22] A. N. Yumang, G. Magwili, D. T. D. A. Coloma, J. M. A. Labuac and J. R. S. Reyes, "A Non-Contact Testing Method for a Switch-mode Power Transformer in an SMPS using Radial Basis Function Neural Network to Analyze Magnetic Flux Leakage Density," 2020 IEEE 12th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM), 2020, pp. 1-6, doi: 10.1109/HNICEM51456.2020.9400021.

[23] A. N. Yumang, L. A. P. Garcia and G. A. Mandapat, "IoT-based Monitoring of Temperature and Humidity with Fuzzy Control in Cherry Tomato Greenhouses," 2023 15th International Conference on Computer and Automation Engineering (ICCAE), Sydney, Australia, 2023, pp. 480-485, doi: 10.1109/ICCAE56788.2023.10111404.

[24] Y. Zhou, H. Mao, and X. Zhang, "Hyperspectral imaging technology for detection of moisture content of tomato leaves," 2011 4th International Congress on Image and Signal Processing, 2011, pp. 167-171, doi: 10.1109/CISP.2011.6099906.

[25] X. Xie, L. Xu and X. Li, "Leaf moisture content measurement using polarized active imaging LiDAR," 2017 IEEE International Conference on Imaging Systems and Techniques (IST), Beijing, China, 2017, pp. 1-6, doi: 10.1109/IST.2017.8261557.

[26] H. Wenting, S. Yu, X. Tengfei, C. Xiangwei, & S.K. Ooi. "Detecting maize leaf water status by using digital RGB images" International Journal of Agricultural and Biological Engineering, 7(1), pp. 45-53. 2014.

[27] M. Takase, J.D. "Owusu-Sekyere and L.K. Sam-Amoah. Effects of Water of Different Quality on Tomato Growth and Development" Asian Journal of Plant Sciences, 9: pp, 380-384. 2010. DOI: 10.3923/ajps.2010.380.384