# Plant Growth Stages and Health Monitoring for A Hydroponics System using YOLOv2 for Image Processing Algorithm


Aina Joy B. Florin
Department of Electronics Engineering
*College of Engineering*
*Technological University of the Philippines - Manila*
Philippines
sheenamarie.cardinal@tup.edu.ph

Shaira Angela B. Rivera
Department of Electronics Engineering|
*College of Engineering*
*Technological University of the Philippines - Manila*
Philippines
shairaangela.rivera@tup.edu.ph

Vanessa Mae V. Sabate
Department of Electronics Engineering|
College of Engineering
*Technological University of the Philippines - Manila*
Philippines
vanessamae.sabate@tup.edu.ph

John Calvin C. Tuason
Department of Electronics Engineering|
*College of Engineering*
*Technological University of the Philippines - Manila*
Philippines
johncalvin.tuason@tup.edu.ph

Clifford John DL. Velasco
Department of Electronics Engineering|
*College of Engineering*
*Technological University of the Philippines - Manila*
Philippines
cliffordjohn.velasco@tup.edu.ph



***Abstract*—**



**Keywords—**


## *I.* INTRODUCTION

Growing of plants without soil is made accessible by hydroponics systems, which reduces the environmental effect and preserves both water and space. According to Kozai et al. (2019), Indoor farming has been increasingly popular as a method for producing crops such as leafy vegetables and fruits in a controlled environment. [1] This provides as an alternative for sustainable agriculture. Hydroponic farming has developed popularity in the Philippines in the past few years as a response to the challenges that result from limited availability of land for agriculture and unpredictable weather changes. According to Hamidon et al. (2023), Different indoor lighting conditions can affect the visual appearance of the seedlings, making it difficult for human operators to accurately identify and sort the seedlings consistently. [2] However, close monitoring as well as oversight of growth stages and health conditions is necessary to ensure ideal plant growth and health status in hydroponic environments. Advanced technologies are necessary since traditional monitoring methods more often fail to give timely and accurate findings.

Integration of image processing methods like YOLOv2 provides the possibility to completely transform hydroponic system monitoring. With images captured within hydroponic systems, YOLOv2's real-time object detection capabilities allow to perform automatic detection and classification of plant growth stages and health status. Farmers as well as other agricultural users can improve the utilization of resources and encourage preventative measures by using the features of YOLOv2 to gather important data into the growth and health of their plants. This determines the feasibility and effectiveness of applying YOLOv2 as an image processing tool for plant growth stage and health monitoring in hydroponic systems in particular to improve agricultural productivity and sustainability.

## *II.* BACKGROUND OF THE PROBLEM

The increasing popularity of hydroponics systems as an alternative for sustainable agriculture in the Philippines arises from the challenges posed by limited land availability and unpredictable weather changes. This soil-less cultivation method addresses these issues, offering resource efficiency and reduced environmental impact. Despite the success of hydroponic farming, meticulous monitoring of plant growth stages and health conditions remains essential for optimal results. Traditional monitoring methods often prove inadequate, failing to deliver timely and accurate findings. The limitations of these conventional approaches highlight the critical need for advanced technologies to enhance monitoring capabilities in hydroponic environments. In this context, the application of an image processing algorithm, YOLOv2, emerges as a transformative solution. By enabling real-time object detection and classification of plant growth stages and health status, YOLOv2 stands poised to revolutionize hydroponic farming practices, fostering improved agricultural productivity and sustainability.

Integrating YOLOv2 into hydroponic systems brings a new approach to monitoring and overseeing plant growth. Traditional methods struggle to capture the detailed and ever-changing aspects of plant growth and health in real-time. YOLOv2's ability to detect and identify objects in real-time within hydroponic environments provides an opportunity to automatically recognize different growth stages and health conditions of plants. This advanced technology empowers farmers and agricultural users to gather important data more efficiently, enabling better use of resources and preventive measures. The need for YOLOv2 as an image processing tool for hydroponic systems arises from its potential to improve agricultural practices by increasing accuracy, real-time monitoring, and overall sustainability in plant growth.

## *III.* OBJECTIVES

The study aims to monitor the growth and health of plants in a hydroponics system using yolov2 as the image processing algorithm specifically:

1. To write and create an image-processing software that utilizes the YOLOv5 Architecture that will monitor and identify the type, maturity, and health of plants

2. To write and design a scheduled image-capturing software every twenty-four hours

3. To create a database to store the captured images

4. To achieve a seventy percent accuracy rate for the computer vision

## *IV.* REVIEW OF RELATED LITERATURE

Based on Brown, S.D. et al. (2012), they discussed the fundamental concepts of Field-Programmable Gate Arrays. This study helped in further understanding of Field-Programmable Gate Arrays.

Further, Lou, Y. et al. (2023) stated that, the speed, power usage and accuracy of the Field Programmable Gate Array (FPGA)accelerated CNN. This study helped in further understanding of using FPGA-accelerated CNN for plant disease detection.

Additionally, according to Lowe, M. et al. (2022), smart technology, both in combination with and distinct from artificial intelligence and machine learning, models have been shown to be efficient in automating and tracking the development and condition of these aquatic agricultural systems. In this study, artificial intelligence will be employed as computer vision to recognize the seedlings that will be planted in the system and improve the actuators' parameters to the ideal environment for that particular type of plant.

Furthermore, based on Dappuri, B. et al. (2022), a cloud-based artificial intelligence system is installed. provided with DLCNN, which continuously tracks sensor data and plant disease conditions and notifies farmers using Agri-Hydroponic software as necessary. This study helped in further understanding of the Artificial Intelligence for tracking sensor data and notifying farmers for plant disease conditions.

Moreover, Ho, B. et al. (2017) stated that the use of Deep learning to image and video recognition. It helped in further understanding of Deep learning or deep neural networks on image pattern recognition.

Also, according to O'Shea, K. et al. (2015), the primarily used and fundamental concepts of CNN. It helped in further understanding of the CNN for finding patterns in images to recognize objects, classes, and categories.

Besides, based on Kumar, S. et al. (2021), the plant disease detection using CNN as an important system of improved agricultural production and quality. It helped in further understanding of using CNN on plant disease detection.

Additionally, Zhang, L. et al. (2020) stated that the method to monitor the growth of greenhouse lettuce. It helped in further understanding of the convolutional neural network for monitoring growth rate of plants**.**

## *V.* METHODOLOGY

### A. *Training of Datasets*

The Yolov5 model's convolutional neural network (CNN) was trained and validated using 2808 files.. Out of these, 2370 files were allocated for training the model and the remaining 438 files were set aside for validation. The dataset contained eight different classes - 'Early-Growth', 'Harvest-Ready', 'Healthy', 'Lettuce', 'Mid-Growth', 'Unhealthy', 'Mustard Green', and 'Spinach'. The main goal of the model was to accurately recognize and categorize samples from these specific classes. By training the CNN Yolov5 on over 3000 images across these various plant types and growth and health categories, the aim was to develop a model capable of reliably identifying and classifying new images from these key classes.

Figure 5.1 Training of Datasets

#### a. *Plant Type Identification*

To identify the types of plants, images of different varieties of lettuce, spinach, and mustard green were captured. This study focused on these three plants due to the climate of the settings which are optimal for the growth of the specified plants.

#### b. *Plant Health*

The plants were classified to monitor whether a plant is healthy or unhealthy based on the color of their leaves, their shape, and height.

#### c. *Plant Maturity Level*

For the maturity level, the plants are classified as early-stage, mid-stage, and harvestable. The early-stage indicate the first to fourteen days of its maturity after the germination period which lasts for about fourteen days. The mid-stage shows a growth within fourteen to twenty-eight days and the harvestable stage indicates the readiness for harvesting which usually happens after twenty-eight days.

### B. *Scheduled Image-capturing software*

The scheduled image-capturing software was designed using the tool, *Crontab*. This task scheduler of Raspberry Pi enabled the capture of images every twenty-four hours to gather data needed to monitor the plants. When the set time was reached, the microcontroller will run the codes that will capture the image. These captured images are then processed by the computer vision to identify the type, maturity, and health of the plant.

### C. *Database*

To store the information and images captured during the scheduled time, a database using Firebase was implemented. The captured images will be stored in this database. Then, it will be retrieved for image processing using the computer vision algorithm. The processed image are then stored back to the database, together with the classifications they were set. These are retrieved and sent to the user to inform them of the status of the plants.

### D. *Accuracy of the Model*

To test, train and validate a convolutional neural network (CNN) in the Ultralytics YOLOv5 pre-trained model using 1222 images for plant maturity and 1225 images for plant health, the process involves several steps. First, a representative dataset is created and divided into three sets: training, validation, and testing. Next, the model is then trained on the training images to understand plant-specific properties such as health and maturity. The model is then evaluated and fine-tuned using the validation images. Finally, the test set is used to examine the model's generalizability. This iterative process of training, validating and testing ensures an accurate and reliable CNN YOLOv5 model is developed for detecting plant health and maturity level. By going through these phases with a sufficient dataset, the model can be optimized to perform well in analyzing new plant images.

## *VI.* RESULTS AND DISCUSSION

### A. *Accuracy of the Trained Model*

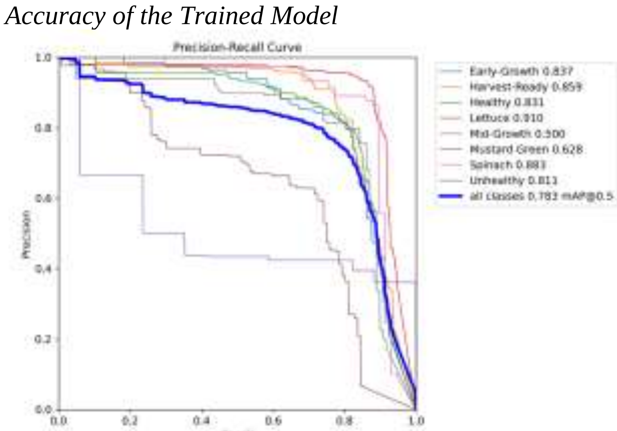

Figure 6.1 Accuracy of the trained model

In Figure 4.4, the trained model's accuracy for Plant Health and Maturity Level Detection was displayed. The graph represents the accuracy of each class where the precision, as shown on this graph, measures how many detections made are correct, while recall measure what percentage of total objects are detected. The accuracy of the plant health and maturity level detection model was utilized to evaluate and test the functionality using the sampled images and plants from the hydroponics system.

Table 6.1 Accuracy of the trained model

| Class | Accuracy(%) |
|---|---|
| Lettuce | 91 |
| Mustard Green | 62.8 |
| Spinach | 88.3 |
| Early-Growth | 83.7 |
| Mid-Growth | 50 |
| Harvest-Ready | 85.9 |
| Healthy | 83.1 |
| Unhealthy | 81.1 |

Table 4.1 demonstrates the trained model's accuracy in disease detection. The accuracy for Lettuce is around 91%, Mustard Green is around 62.8%, and Spinach is 88.3%. The lower accuracy for Mustard Green is due to the limited dataset for that vegetable. The proponents are still gathering more data for Mustard Green to improve the accuracy. The table also shows the accuracy for Early Growth, Mid Growth, and Harvest Ready stages, which are currently 83.7%, 50%, and 85.9%, respectively. Finally, it displays the accuracy for detecting healthy and unhealthy plants, which is 83.1% and 81.1%, respectively. The proponents are still gathering additional data to enhance the overall accuracy of the model.

## *VII.* CONCLUSION

In this study an image processing software that utilizes the YOLOv5 Architecture that will monitor and identify the type, maturity, and health of plants was successfully written and created. A scheduled image-capturing software was also created that will then be processed in the computer vision. All these images, captured and processed, are stored in the database implemented using Firebase. The accuracy of the model was measured and demonstrated high results with identifying lettuce, mustard green, and spinach with 91%, 62.8%, and 88.3% accuracy. It also shows promising accuracy with detecting the plant growth from early to harvest-ready stage. And, a great accuracy were also given when detecting the plant health.

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