HydroMAC: Crop Status and Disease Detection of Indoor Hydroponic Crops via YOLOv5 Algorithm

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***Abstract*— The field of agriculture has experienced significant advancements with the adoption of deep learning technology. This research explores the application of Convolutional Neural Networks (CNNs) in agriculture for crop disease detection and growth assessment. Using image-based approaches and deep learning techniques, the study collected datasets of crop growth phases, focusing on spinach, bok choy, and romaine lettuce, with an emphasis on diseased crops. The You Only Look Once (YOLOv5) model was used for training and testing, supported by data annotation and augmentation with Roboflow. The trained model achieved high accuracy, with an average precision (AP) score of 0.917, indicating effective identification of positive instances while minimizing false positives. The precision-recall curve confirmed the model's success in accurately classifying positive instances across various recall levels. Implementing CNNs for crop disease detection and growth assessment holds great potential for improving agricultural practices. By leveraging deep learning technology, farmers can enhance crop quality and efficiency. This research contributes to advancing reliable and secure food production through the adoption of advanced agricultural technologies.**

Keywords— YOLOv5, Convolutional Neural Networks, diseased crops, crop growth, hydroponics

I. INTRODUCTION

Over time, the field of agriculture has witnessed the expansion of deep learning technology. [1]. Advanced agricultural technology, leveraging deep learning, has emerged to enhance the production of reliable and secure food. Various studies have employed diverse algorithms, including the notable convolutional neural network (CNN) that has gained prominence in computer vision applications, such as visual imagery analysis. CNN incorporates essential components like convolution layers, pooling layers, and fully connected layers to learn spatial hierarchies of data autonomously and adaptively through the process of backpropagation [2, 3]. One area where deep learning phenomena, such as CNN, has shown its potential is in the detection and analysis of leafy plants' growth patterns. Imagebased approaches have been widely deployed for nondestructive monitoring of agricultural growth, allowing for more accurate and efficient assessments. The utilization of CNN for analyzing different crop diseases has yielded significant findings, enabling advancements in the production of crops with improved quality and efficiency. These studies have proven to be highly beneficial for the agricultural industry.

II. RELATED STUDIES

A recent examination of multiple studies focused on the potential of deep learning algorithms in detecting agricultural diseases. The outcomes show encouraging prospects for advancing agricultural technologies, which could contribute to the production of food that is both sustainable and secure [4]. In a 2019 study, basic methods of visualizing plant diseases were found ineffective, while advanced techniques showed promise. Feature visualization and a semantic dictionary extracted significant visual features for disease classification. Human evaluation and expert knowledge in plant science remained essential for accurate assessment [5]. Paymode and Malode used CNN techniques to detect MultiCrops Leaf Disease (MCLD). Their study successfully classified diseased and healthy leaves using a deep learningbased algorithm and the VGG model. A dataset of cropped leaf images was utilized for training and testing. The results showed accuracies of 98.40% for grapes and 95.71% for tomatoes [6]. In a 2016 report, a trained algorithm was able to classify 14 crops and 26 diseases with an accuracy of 99.35% [7].

In a study, depth wise separable convolution was used instead of standard convolution in the inception block, reducing parameters. Four deep learning models (InceptionV3, InceptionResnetV2, MobileNetV2, and EfficientNetB0) were employed to detect plant diseases using images of healthy and diseased leaves. The EfficientNetB0 model achieved the highest accuracy of 99.56%, while requiring less training time compared to other models [8]. Furthermore, a study explored the use of a pre-trained ResNet34 model for detecting crop diseases. They established a dataset consisting of 8,685 leaf images captured under controlled conditions to train and validate the model. The validation results indicated that the proposed method achieved an accuracy of 97.2% and an F1 score exceeding 96.5% [9].

Deep learning, specifically CNN, is applied to detect growth-related characteristics in leafy vegetables, representing a notable application in the field [10]. Imagebased techniques, powered by computer vision technology, are extensively used for nondestructive agricultural growth monitoring. These techniques have gained popularity due to their ability to measure important growth indices such as leaf fresh weight (LFW), leaf dry weight (LDW), and leaf area (LA) [11]. In [10], a CNN model was employed to establish the relationship between photos and their corresponding growth-related attributes. The results demonstrated that the CNN model was successful in accurately estimating the growth-related characteristics. This indicates the effectiveness of CNN in obtaining precise estimations of these attributes based on the provided photos.

III. METHODOLOGY

The datasets collected consist of snapshots of the crops' growth phases through the cameras installed inside an automated indoor hydroponics system. Each dataset from diseased crops was collected from the cloud. The crops planted in the system are spinach, bok choy, and romaine lettuce. The You Only Look Once (YOLOv5) model was used to train the datasets.

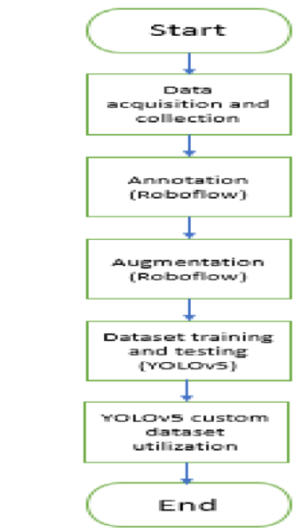

Fig. 1. Process Flowchart

Fig. 1 shows the overall process flowchart of the study. The datasets collected will be annotated and augmented using Roboflow. The datasets are then trained and tested using the YOLOv5 algorithm. The custom datasets are then utilized.

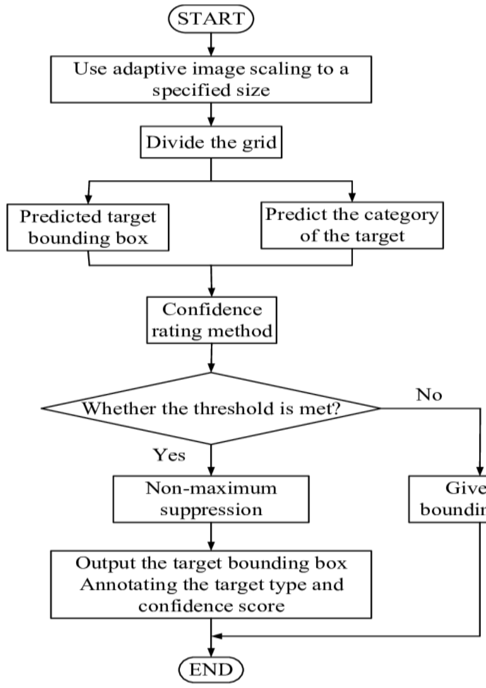

Fig. 2. YOLOv5 Target Detection Flowchart

The YOLOv5 target detection flowchart shown in Fig. 2 involves several steps. First, the input image is preprocessed and passed through a backbone network to extract high-level features. The feature maps are then generated. The feature maps are used by detection heads to predict bounding boxes, class labels, and confidence scores for potential objects. Finally, the algorithm outputs the detected objects along with their bounding boxes, class labels, and confidence scores.

A. Data Acquisition and Collection

In the three-layer hydroponics system situated at the barangay hall in San Miguel, Taguig, three cameras were strategically installed on the right side of each layer. The bottom layer accommodates spinach plants, the middle layer houses bok choy plants, and the top layer is designated for romaine lettuce cultivation.

Fig. 3. Hydroponics chamber

Fig. 3 shows the hydroponics chamber where the crops are planted. It is in a barangay hall in Barangay San Miguel, Taguig.

Fig. 4. Xiaovv By V380 Webcam USB Camera

Fig. 4 shows the camera installed in the system used for dataset acquisition.

TABLE I. CAMERA SPECIFICATIONS

Camera Weight	110 g
Size	100 x 25 x 50 mm
Working Temperature	-10 °C to 50 °C
Resolution	1024
Viewing Angle	150 °

Table I displays the specifications of the camera used in the system.

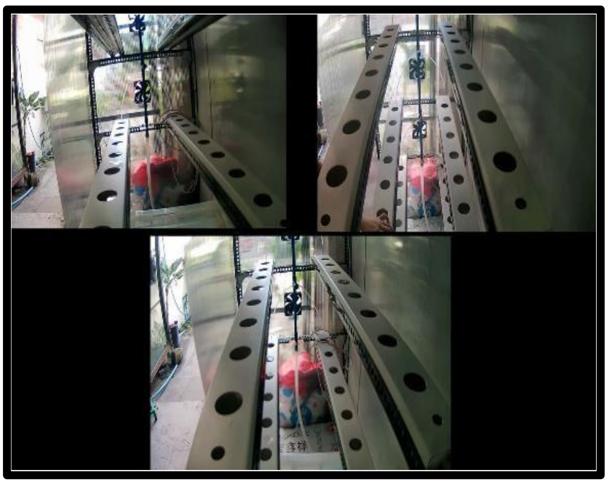

Fig. 5. Viewing angle of the camera

Fig. 5 shows the viewing angle of the cameras. The cameras are mounted to the right side of the system. Images taken by the camera in this angle will be fed to as dataset for the YOLOv5 model.

Fig. 6. Sample dataset

Fig. 6 shows a sample from the data sets collected. The parameters such as brightness and color are considered in taking dataset images. Using a fixed setting allows researchers to establish a standardized process for capturing images. This helps to eliminate variations in image quality, lighting conditions, camera settings, and other factors that can affect the interpretation and analysis of the data to the YOLOv5 Model.

TABLE II. DIVISION OF DATASETS

Category		**Number of images used as datasets**
Diseased	Spinach	1064
	Bok choy	1111
	Romaine Lettuce	1400
Not ready to harvest	Spinach	1114
	Bok choy	1808
	Romaine Lettuce	636
Ready to harvest	Spinach	2172
	Bok choy	2511
	Romaine Lettuce	2172

Table II shows the division of datasets used in the study. Images are taken and classified whether they are diseased, not ready to harvest, or ready to harvest.

B. Annotation

The images collected are annotated using Roboflow. Classes and labels are set in this process. A total of 9 classes were used in the study.

Fig. 7. Pre-processing sample dataset annotation

Fig. 7 shows an image of a diseased spinach acquired from the cloud used in the preliminary annotation of preprocess sample data set.

Fig. 8. Image annotation using Roboflow

Fig. 8 shows the annotation of not-ready-to-harvest bok choy plants using Roboflow.

Fig. 9. Pre-processing sample dataset for lettuce

Shown in Fig. 9 is a store-bought harvested lettuce used for the preliminary annotation of preprocess ready-to-harvest lettuce dataset.

C. Augmentation

To multiply the datasets into a factor of three, the images fed in the Roboflow annotation will be augmented. This process involves the rotation of each image three times. This ensures high accuracy and precision of the trained model.

D. Dataset Training and Testing

The datasets from Roboflow are then fed to the YOLOv5 algorithm. 70% of the datasets are assigned for training, 10% for validation, while the remaining 20% is for testing. The codes from the Colab file are used to train the custom datasets from YOLOv5.

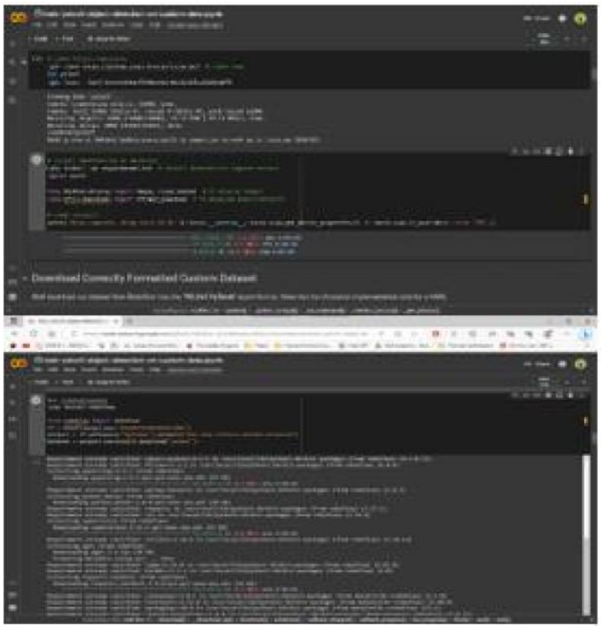

Fig. 10. Training of datasets

Fig. 10 shows the downloading of the necessary requirements for training the datasets.

E. YOLOv5 Custom Dataset Utilization

To use the weights from the custom dataset, the firmware of the Raspberry Pi is updated, along with the necessary Python packages and dependencies. This installation enables the use of YOLOv5 and OpenCV, Python packages, on the Raspberry Pi, allowing screen capturing. The screen captures are uploaded to a Google Drive for viewing. To fully utilize YOLOv5, the YOLOv5 repositories are cloned from GitHub using a terminal application on the Raspberry Pi. Once cloning is complete, the weights from the trained datasets are downloaded onto the Raspberry Pi. Subsequently, codes that utilize the trained datasets and take screenshots are created. Finally, one of the codes is run in a Python IDE, and the other code in a Terminal Application.

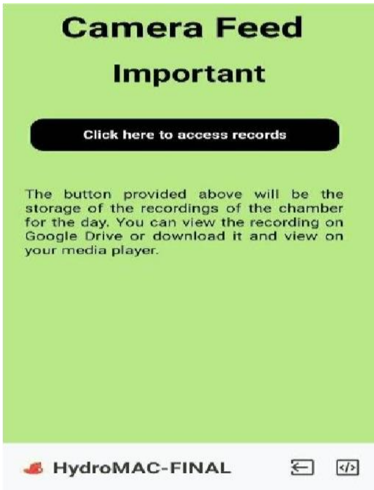

Fig. 11. Custom mobile application for image detection output

Fig. 11 shows the mobile application tab where the outputs of the utilized YOLOv5 trained models can be viewed and accessed.

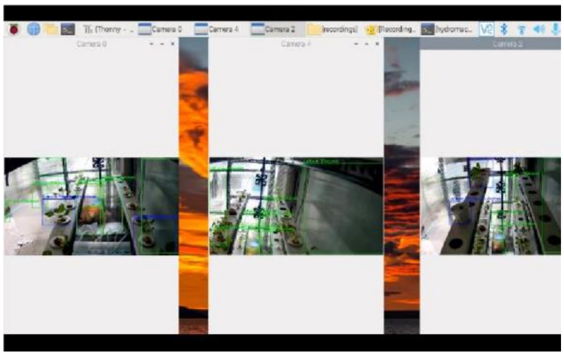

Figure 12. Output of dataset utilization

Fig. 12 shows the output of the custom YOLOv5 datasets. The snapshots of the crops inside the hydroponics chamber are detected and then classified.

IV. RESULTS AND DISCUSSION

The datasets underwent training for a total of 100 epochs, a methodology that yielded highly effective outcomes for the implemented model.

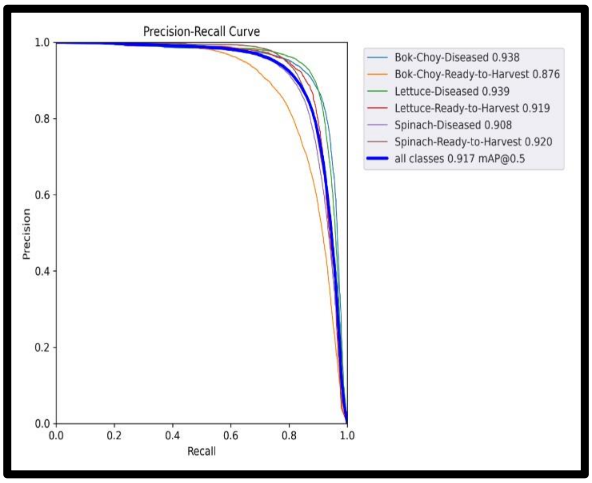

Fig. 13. Precision-Recall Curve of Trained Datasets

The precision-recall curve in Fig. 13 demonstrates how well the evaluated model performs in terms of precision and recall. With an average precision (AP) score of 0.917, the model shows a high level of accuracy in identifying positive instances while minimizing false positives. The x-axis represents the range of recall values from 0 to 1, while the yaxis represents the corresponding precision values. The curve illustrates a favorable balance between precision and recall, indicating the model's effectiveness in accurately classifying positive instances.

The mAP value of 0.917 implies that, on average, the model achieves a high precision rate for positive predictions across different levels of recall. This means that when the model makes predictions with a threshold of 0.5, it tends to accurately identify positive instances while minimizing false positives. The mAP serves as a comprehensive metric for evaluating the overall performance of the precision-recall curve. It considers precision values at various recall levels and provides a single numerical score to assess the model's effectiveness in the given task. A higher mAP indicates better overall precision-recall performance.

V. CONCLUSION

The efficient utilization of a Convolutional Neural Network (CNN) model for identifying diseases and assessing crop status through image analysis serves a valuable purpose. By harnessing the power of deep learning, this model can effectively analyze and interpret visual data to accurately detect and categorize crop diseases in hydroponic chambers. CNN’s capacity to learn and identify patterns within images allows it to offer insightful information regarding the well-being, developmental stage, and overall condition of plants.

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