# Vision-Based Object Detection for Efficient Monitoring in Smart Hydroponic Systems

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**Abstract.** With the advancements in technology, smart hydroponic systems have gained popularity as an efficient and sustainable method of cultivation. These systems allow for precise monitoring and control of various parameters such as nutrient levels, pH, temperature, and humidity. To further improve the monitorin capabilities of smart hydroponic systems, integrating object detection using vision-based techniques is proposed. This integration aims to enhance the monitoring process by enabling the system to identify and track specific objects or elements of interest. In this paper, we propose a modified, yet lightweight, object detection model based on the YOLO-v8 architecture.

The proposed model can detect 'ready', 'empty pod', 'germination', 'pod', and 'young' on the hydroponics palate. The experimental results also demonstrate that precision is improved by a large margin. In fact, as shown in the experiments, the results show a 0.91 score for F1-Confidence curve. Recall rate at different probability thresholds with all classes 91% confidence with F1 over 0,8 except “ready” class.

**Keywords:** YOLO, smart hydroponics, AI, object detection.

## 1. Introduction

Smart Hydroponic Systems are a modern approach to agriculture that utilizes advanced technology and automation to grow plants without soil [1]–[3]. One key aspect of these systems is the use of water-based nutrient solutions to provide plants with essential nutrients. To effectively monitor and manage the growth of plants in smart hydroponic systems, it is crucial to integrate object detection using visionbased techniques[4]. Integrating object detection using vision-based techniques in smart hydroponic systems allows for real-time monitoring and analysis of plant health, growth patterns, and the presence of any pests or diseases[5]. Moreover, vision-based object detection can


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provide valuable insights into the overall performance of the hydroponic system by tracking and analyzing various parameters such as water levels, nutrient levels, and environmental conditions. By implementing object detection using vision-based techniques, smart hydroponic systems can achieve higher levels of efficiency and productivity. The controlled environment of smart hydroponic systems allows for optimization of growing conditions, leading to higher plant yields and better product quality[6]. Additionally, the use of hydroponic systems in agriculture is becoming increasingly popular due to their ability to be operated automatically and easily integrated with technologies such as web-enabled smart devices[7].

Object detection is a computer vision technique that involves identifying and localizing objects within an image or video. This is typically achieved through the use of machine learning algorithms that are trained to recognize specific objects or classes of objects. These algorithms analyze the visual features of an image or video frame and classify them based on predefined patterns or characteristics. In the context of smart hydroponic systems, object detection using vision-based techniques refers to the ability to identify and track various entities within the system, such as plants, pests, diseases, and environmental parameters. By utilizing object detection techniques, smart hydroponic systems can automatically detect and locate these entities, providing valuable information for growers to make informed decisions about their cultivation practices and take necessary actions to ensure plant health and optimal growth. Integrating object detection using vision-based techniques in smart hydroponic systems allows for real-time monitoring and analysis of plant health, growth patterns, and the presence of pests or diseases.

Vision-based techniques offer a range of tools and algorithms for monitoring hydroponic systems. These techniques involve capturing images or videos of the plants and their surrounding environment and applying image processing algorithms to extract relevant information. These can include techniques such as image segmentation, feature extraction, and object recognition. When applied to smart hydroponic systems, vision-based techniques can provide valuable insights into various aspects of the system's operation and plant health. For example, vision-based object detection can be used to monitor the growth and development of plants by analyzing factors such as leaf size, color, and shape. Additionally, it can be used to detect and track pests or diseases by identifying abnormal patterns or discoloration in the plants. Integrating object detection using vision-based techniques in smart hydroponic systems offers numerous benefits for monitoring and managing the system. It allows for automated and continuous monitoring of plant health and growth, reducing the need for manual inspections. Furthermore, by providing real-time information on the presence of pests or diseases, it enables growers to take timely actions to mitigate the risks and prevent further damage to their crops.

In the other works, various monitoring techniques for smart hydroponic systems have been described. One example is the autonomous computer vision-guided plant sensing and monitoring system developed by David and Murat, which continuously monitors temporal, morphological, and spectral features of lettuce crops in a nutrient film technique hydroponics system [1]. This system combines computer vision technology with hydroponics to provide comprehensive monitoring and analysis of plant growth and health. Another example is the hydroponic monitoring and automation system with a web interface management system, as described in the literature. This system allows users to monitor and control NFT hydroponic farming using a responsive web framework[8]. Furthermore, the development of embedded, portable analyzers with sensor arrays has enabled direct measurement of nutrient concentrations in hydroponic solutions[9]. These monitoring techniques showcase the importance of integrating object detection using visionbased techniques in smart hydroponic systems. Object detection using vision-based techniques in smart hydroponic systems offers numerous benefits for monitoring and managing the system.

While vision-based techniques for monitoring hydroponic systems offer advantages in terms of automated and continuous monitoring, there are limitations that need to be considered. One limitation is the complexity and cost associated with implementing and maintaining such systems. Vision-based object detection requires specialized hardware and software, as well as skilled personnel to operate and troubleshoot the system. This can add to the overall expenses and may not be feasible for small-scale growers with limited resources. Another limitation is the accuracy and reliability of the object detection algorithms. Vision-based techniques heavily rely on the accuracy of image processing algorithms to detect and track entities such as pests or diseases. However, these algorithms may integration of object detection in hydroponic systems pose challenges in accurately identifying and distinguishing between different objects or abnormalities.

## 2. Related Work

YOLO (You Only Look Once) is a real-time object detection algorithm that can be used for various applications such as selfdriving cars, surveillance systems, and facial recognition software. In recent years, researchers have also explored its application in agricultural settings, including smart hydroponic systems. Smart hydroponics refers to the use of advanced technology and automation to optimize crop growth in controlled environments. By using sensors, actuators, and other devices, these systems aim to provide optimal conditions for plant growth, maximizing yields and minimizing waste.

Plant detection using YOLO in smart agriculture, especially in hydroponic systems, is a promising approach to automate the identification of plant diseases and optimize crop productivity. Park and Kim (2021) designed and developed a system for monitoring the strawberry cultivation environment in real-time and providing enhanced information about harvesting timing to decision-makers. The system collects, stores, and visualizes strawberry growing environment data, and uses a deep learning algorithm (YOLO) to classify the maturity level of strawberries in images. The algorithm achieves a high accuracy rate of 98.267% in predicting the harvest time [10].

Wang and Liu (2021) developed a YOLO-Dense model for tomato anomaly detection in a complex natural environment. The model incorporated a dense connection module to improve network inference speed and multiscale training strategy to improve recognition accuracy at different scales. Experimental results show that the YOLO-Dense model outperforms other models in tomato anomaly detection under complex natural environments, achieving a mean average precision (mAP) of 96.41% and a detection time of 20.28 ms per image [11].

Hamidon and Ahamed (2022) presents an automated detection method for tipburn lettuce grown indoors using deep learning algorithms based on a one-stage object detector. The study evaluates three different one-stage detectors, namely CenterNet, YOLOv4, and YOLOv5, for detecting tip-burn on lettuce grown in indoor farms under different lighting conditions. In the training dataset, all the models exhibited a mean average precision (mAP) greater than 80% except for YOLOv4. The most accurate model for detecting tip-burns was YOLOv5, which had the highest mAP of 82.8%. In addition, the performance of the trained models was also evaluated on images taken under different indoor farm light settings, including white, red, and blue LEDs. Again, YOLOv5 was significantly better than CenterNet and YOLOv4 [12]. Zhang and Li (2022) propose a novel method called YOLO-VOLO-LS (based on YOLOv5) for variety identification of lettuce seedlings in the early growth stage. The method combines the advantages of target detection and target classification mechanisms to accurately identify different varieties of lettuce at the SP stage. The study found that the performance of the lettuce variety classification model in the SP stage needs improvement, which led to the proposal of the YOLO-VOLO-LS method. The results show that the method achieves excellent results in terms of accuracy, recall, precision, and F1-score, with values of 95.961, 93.452, 96.059, and 96.014, respectively. This novel method has a certain reference value for accurately identifying varieties in the early growth stage of crops [13].

These studies demonstrate the potential of YOLO in smart hydroponic systems for crop detection, providing better information on harvest time, and improving efficiency in farm management.

## 3. Method

The methodology for the implementation of the algorithm will be based on the block diagram shown in Fig. 1.

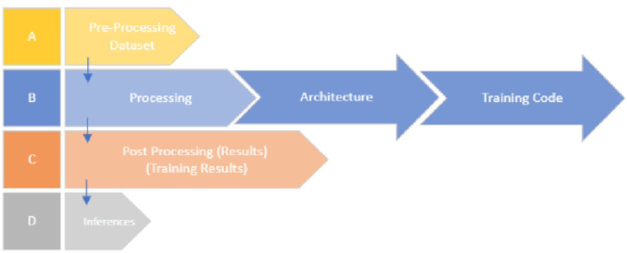


**Fig. 1**. Methodology.

## 3.1. Preprocessing

To build and test our approach we collected a set of images from the RoboFlow. This dataset was originally created by Rinat Landman [14]. The database for the detection lettucepallets consists of a total of 1286 RGB images taken with a 13MP/M2MP camera with dimensions of 1920*1080 pixels between 'ready', 'empty pod', 'germination', 'pod', and 'young' leaf. These images are divided into 3 subgroups train (1060 images), test (151 images), and valid (299 images) respectively. Therefore, the samples acquired for training are of the trinity type as shown in Fig. 2.

**Fig. 2.** Sample image of dataset.

## 3.2. Processing

In this processing part, a state-of-the-art object detection algorithm called YOLOV8 is being utilized to implement object detection in smart hydroponic systems. The integration of YOLOV8 aims to accurately identify and classify various objects of interest such as conditions on planting hole 'Ready', 'empty_pod', 'germination', 'pod', 'young'. This integration will enhance the monitoring capabilities of the system, providing real-time information on plant health and status. Consequently, farmers or system operators can promptly take appropriate actions based on the detected objects, adjusting nutrient levels, applying pesticides, or implementing preventive measures as necessary. Integration of vision-based techniques for object detection in smart hydroponic systems has practical applications for effective system monitoring and management.

The YOLO algorithm presents an effective method for achieving more precise bounding boxes. To achieve this, the input image is divided into a grid structure. In practical application, a more refined grid, such as a 9 by 9 grid, is employed. Each of these grid cells undergoes image classification and localization algorithms. This entails assigning a label Y to every grid cell, represented as an n-dimensional vector. The n-dimensional vector encompasses several attributes, including PC which is set to 0 or 1, indicating the presence of an object in that specific grid cell. The network identifies four parameters - $b_x$, $b_y$, $b_h$, $b_w$ - to define the bounding box, but only when there exists a disease pattern associated with the respective grid cell. These parameters are utilized to define the characteristics of the bounding box. $b_x$, $b_y$ = Offset from the top left corner of the image $b_h$ = Height of the bounding box, $b_w$ = Width of the bounding box.

These parameters are explained and depicted in Fig. 3. Mathematically,

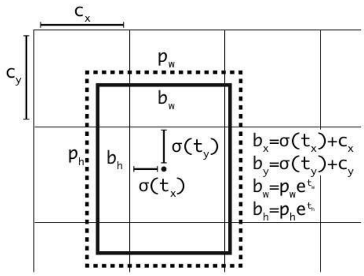


**Fig. 3.** Predicting the box coordinates.

### 3.3. Post-Processing

Post-Processing is one of the future perspectives of visionbased object detection in hydroponic systems is the refinement of post-processing techniques for object detection algorithm outputs. Post-processing techniques can further improve the accuracy and reliability of object detection results in hydroponic systems. These techniques include filtering out false positives, enhancing object localization, and improving object tracking. The YOLOv8 algorithm outputs can be refined to provide more precise and consistent object detection results in smart hydroponic systems.

YOLOv8 generates predictions in the form of bounding box coordinates $t_x$, $t_y$, $t_w$, $t_h$ confidence, and class probability. The coordinates ($t_x$, $t_y$) represent the center of the box relative to the cell's side, while ($t_w$, $t_h$) predict the overall height and width of the image. Confidence represents the Intersection over Union ($IoU$) between the predicted box and the ground truth box. To obtain the final prediction, the determining factor is the class confidence score, which is based on the conditional probability of the class and the box confidence score. The class confidence score measures the confidence value in object classification and localization. It provides a specific class confidence value for each box, encoding the likelihood of the class appearing in the box and how well the predicted box corresponds to the object. If no objects are detected, the confidence value is zero. Intersection over Union ($IoU$) can be calculated by comparing the groundtruth bounding box and the predicted bounding box, which can be expressed using the equation:

$$IoU = \frac{Area\ of\ overlap}{Area\ of\ union}$$

In addition to the $IoU$ value, the average $IoU$ value is also obtained, known as the mean average precision (mAP). In this study, mAP@ $IoU$ requires a threshold value exceeding 0.5 to be considered successful. If the value is less than 0.5, the result can be considered incorrect. For the threshold set at 0.5, the following is known:

If IoU ≥ 0.5, classify the object as True Positive (TP).

If IoU < 0.5, classify the object as False Positive (FP).

If the ground truth displays an object, and the model fails to detect the object, classify it as False Negative (FN).

Any part of the image not detected should be classified as True Negative (TN).

The above values can be used to calculate precision and recall using the equation:

$$Precision = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + False\ Positives\ (FP)}$$

Recall, also known as sensitivity or true positive rate, is the ratio of true positive predictions to the total number of actual positive instances.

$$Recall = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + False\ Negatives(FN)}$$

From the calculation of $IoU$, obtain True Positive, False Positive, and False Negative values used to calculate the precision and recall scores from the object detection results of lettuce pallets. The precision and recall values are then depicted on a curve known as the precision-recall curve. The Average Precision (AP) value itself is obtained from the calculation of the area under the curve for each detected class in the system. Meanwhile, the mean Average Precision (mAP) value is obtained by averaging the AP values from all detected classes.

## 3.4. Inferences

This is the final process of using a trained YOLOv8 model to predict the presence of objects in an image or video frame. During inference, the model takes an input image as input and processes it through its neural network architecture to make predictions about the objects present in the image. The predictions made by YOLO may result in multiple bounding boxes for the same object or overlapping predictions. To filter out redundant and low-confidence predictions, a post-processing step is applied. Non-maximum suppression (NMS) is a common technique used to remove duplicate and overlapping boxes, keeping only the one with the highest confidence. The final output of the YOLO inference process is a list of bounding boxes, each associated with a class label and a confidence score. These bounding boxes represent the objects detected in the input image. The NMS process can be summarized using the following equation:

$$NMS(B) = \{ b \in B : confidence^{(b)} \geq confidence^{(a)}, IoU(b,a) \leq IoU\_threshold\ for\ all\ a \in B\ where\ a \neq b \}$$

Where:

$B$ is the list of sorted bounding boxes.
$b$ and $a$ are individual bounding boxes in the list.
$confidence(b)$ is the confidence score of box
$IoU(b, a)$ is the Intersection over Union between boxes $IoU\_threshold$ is the threshold value for IoU, usually set to 0.5.

The resulting set $NMS(B)$ contains the bounding boxes that have survived the non-maximum suppression process and are considered the final predictions.

# 4. Result And Discussion

In this section, we present an overview to the dataset, experiments conducted and the results.

## 4.1. Experiment Dataset

To build and test our approach we collected a set of images from the RoboFlow. This dataset was originally created by Rinat Landman [14]. This portion introduces the outcomes of the study conducted on the dataset shown in Figure 4 .

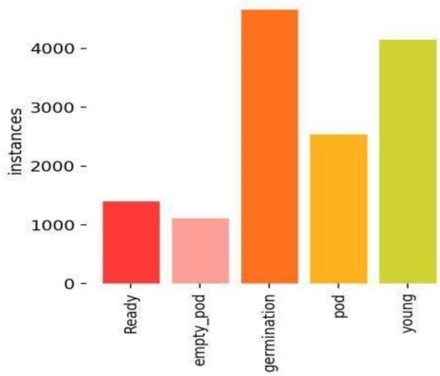


**Fig. 4.** Predicting the box coordinates.

Confusion matrix normalized to evaluate the performance of the integrated system in accurately detecting and classifying objects in a hydroponic environment shown in Figure 5. To evaluate the performance of the integrated system in accurately detecting and classifying objects in a hydroponic environment, a confusion matrix was normalized. The integration of object detection using vision-based techniques in smart hydroponic systems has practical applications for monitoring and managing the system. The condition ready, empty_pod, germination, pod, young and background related predicted. The condition of the objects, such as ready, empty_pod, germination, pod, young, and background, were predicted and evaluated using a normalized confusion matrix.

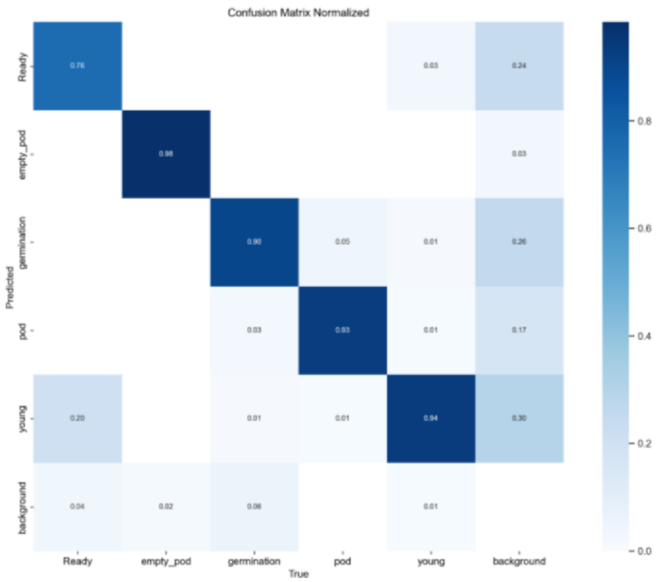


**Fig. 5.** Confusion matrix normalized.

## 4.2. Training Model

The experiments and tests were conducted on a server equipped with a GeForce GTX1030 T1 GPU, an Intel(R) Core(TM) i7-10700F CPU @ 2.90GHz 2.90 GHz CPU, and running 64-bit Windows 10. The PyTorch framework and Python 3.9 were used for the experiments. The model was trained using GPU acceleration, while the tests were conducted using both GPU acceleration and CPU. This section presents a comprehensive performance analysis of the custom YOLO model, which is based on the YOLOv8s framework. Figure 6 shows the training set loss function of the custom YOLOs model plotted against the training iteration rounds (epochs).

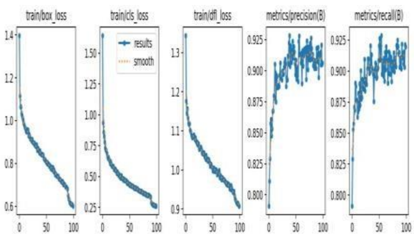


**Fig. 6.** Predicted training bounding box regression loss, object confident loss, and object classfication loss

However, when applied to the initial datasets of lettuce-pallets, the achieved mean Average Precision (mAP) at IoU thresholds between 0.5 and 0.95 was 72,8% for all class. Furthermore, for the same datasets, a mAP50 of 95% was achieved. It is important to note that the original data labeling provided was deemed unreliable upon closer examination, as previously indicated, due to the method of generation. Consequently, the reliability of these results is contingent on the accuracy of the mask labeling. The F1 confidence curve provides a measure of the integrated system's accuracy in detecting and classifying objects within a hydroponic environment. This curve is generated by plotting the F1 score, which considers both precision and recall, against different confidence thresholds. The F1 confidence curve allows for the evaluation of the integrated system's accuracy in detecting and classifying objects within a hydroponic environment. All classes shown 0.91 score for F1Confidence curve. The curve shown in picture figure 7.

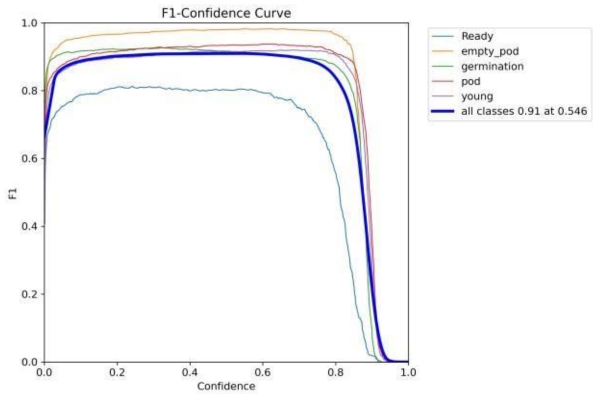


**Fig. 7.** F1-confidence curve

## 4.3. Precision and Recall Result

The precision-recall curve is a useful tool for assessing the performance of the integrated system in terms of object detection and classification accuracy in a hydroponic environment. The curve as shown figure 8, plots the precision rate against the recall rate at different probability thresholds with all classes 91% confidence with F1 over 0,8 except "ready" class. By analyzing the precision-recall curve, the tradeoff between precision and recall can be observed for varying thresholds. Furthermore, the precision-recall curve result an optimal classification threshold that provides satisfactory precision and recall performance. All of precision and recall performance curve already shown in figure 8.

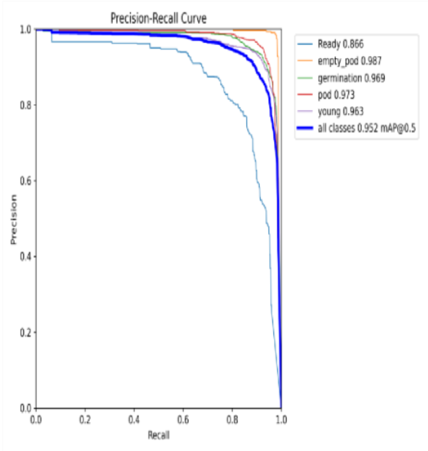


**Fig. 8.** Precision-recall curve

The recall-confidence curve is an important metric used to evaluate the performance of the integrated system in accurately detecting and classifying objects in a hydroponic environment.

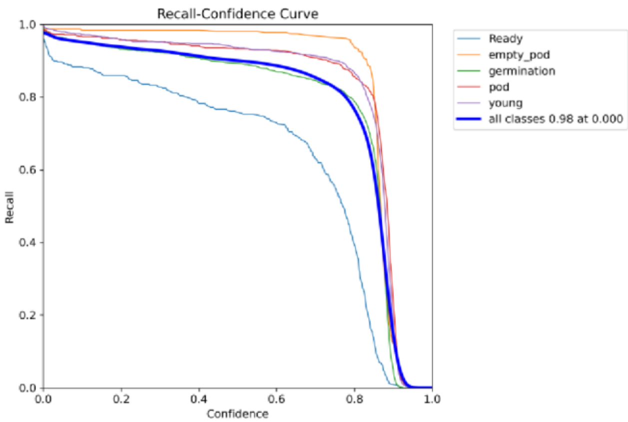


**Fig. 9.** Recall-confidence curve

The recall-confidence curve provides insights into the integrated system's ability to accurately detect and classify objects within a hydroponic environment at different levels of confidence. This evaluation metric is essential in evaluating the performance of the integrated system in accurately detecting and classifying objects within a hydroponic environment. Based on figure 9, the recall-confidence curve shows that as the confidence threshold increases, the recall rate also increases. This indicates that the system can correctly identify a higher proportion of objects as the confidence in their detection increases. Integrating object detection using visionbased techniques in smart hydroponic systems has practical applications for monitoring and managing the system.

We have obtained the following results as shown in Figure 10. On training the model up to 100 epochs the model has predicted with high accuracy for detection conditions on planting hole 'Ready', 'empty_pod', 'germination', 'pod', 'young'.

**Fig. 10.** The result of detection object with class

## 5. Conclusion And Future Works

In conclusion, the integration of object detection using vision-based techniques in smart hydroponic systems has shown promising results in terms of accurately detecting and classifying objects within a hydroponic environment. The recallconfidence curve provides insights into the system's ability to detect and classify objects accurately in a hydroponic environment at different confidence levels. Overall, the precision-recall and the recall-confidence result provide valuable insights into the performance of the object detection and classification model in the smart hydroponic environment. These evaluation metrics allow us to understand the system's accuracy and ability to correctly identify objects, which is crucial for monitoring and managing the hydroponic system effectively especially for "ready" class. However, this preliminary research still has some limitations. Besides the dataset used is still too small, the amount of data portion in each class is also not balanced. Therefore, combinations with similar datasets and the application of various augmentation techniques need to be done.

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