RESEARCH ARTICLE

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An example of lettuce (*Lactuca Sativa*) seedling selection using deep learning method for robotic seedling selection system

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Abstract

Lettuce is a type of vegetable that is widely cultivated and consumed in our country and in the world. The seedling period, which is the beginning of production, is the most sensitive time for the plant. Starting production with healthy seedlings is an important parameter for quality and efficient production. In this study, a sample program for automatic seedling selection was developed for a robotic system to be used in seedling production. With the developed program, it was aimed to select seedlings with the same degree of maturity in multi-well pots. In this study, Yolo5n was used for the training model. A learning system was established on two types of lettuce (curly salad), and red curly lettuce leaf (lolo-rosso) seedlings. As a result of the training, F1 score was found as 83%; Precision was 100%; Recall was 95%; Precision Recall was 86.7%. The learning rate was 0.0005 for all given images. In view of these data, positive results were obtained for the mentioned method in seedling selection.

Keywords: Deep learning, Lettuce, Robotics

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INTRODUCTION

Lettuce (*Lactuca sativa*) is a cool climate vegetable from the Asteraceae (Compositae) family, widely produced worldwide, whose leaves is eaten and can be grown year-round in open and under cover. Since it can be produced all year round, it can be easily alternated with different vegetables. It can also be grown on small home balconies and in large areas. The lettuce group is a vegetable of high economic value that is consumed as a salad ingredient in the world. However, in some countries such as China, the roots and leaves are also eaten cooked (Anonymous,2023a). Lettuce is one of the vegetables that are not very selective in terms of soil requirements. It can be grown in all kinds of soils from light soils to clayey heavy soils. The most important climatic factors in the germination and emergence of lettuce are light and temperature (Vural et al. 2000, Doğru and Çilingir, 2019).

Because of the advantages such as lettuce cultivation can be done by direct seed sowing method, seedling cultivation is more preferred. There are some quality characteristics that producers look for in ready seedlings. These are; narrow internodes of the seedlings, dark green leaf color, completed root wrapping in peat, thick and strong stem, and high dry matter content of the root and stem (Akdemir, 2018). Production with ready seedlings has reached 100% in greenhouse vegetable production and 70% in open field vegetable cultivation in our country (Yelboğa, 2014).

Seedling production is done in pans, crates and viols according to the growing season. In seedling cultivation, which is carried out by growers within their own means, cultivation with ready seedlings produced in seedling enterprises has been preferred in recent years due to reasons such as failure to provide optimum conditions, failure to carry out maintenance processes in accordance with the technique and high cost. In modern seedling production facilities, seeds are sown untouched with advanced technologies. It has been reported that coated seeds, which are mostly used in lettuce seedling production, provide great convenience in seedlings, reduce seed loss, have a germination rate close to 100% and uniform emergence. Lettuce seeds germinate within 1-3 days at optimum temperature values in germination rooms. Immediately after germination, the vials are transferred to the greenhouse. Since the optimum ecological factors required for lettuce seedling production are easily provided in the greenhouse and maintenance processes such as irrigation, feeding, disease and pest control and growth control are carried out regularly in accordance with the technique, quality seedlings that reach the planting stage in a short time (25-35 days) are obtained (Anonymous, 2023b). In seedling cultivation under producer conditions, seedlings reach planting size in 40-50 days depending on the production period, while ready seedlings reach planting size between 25-35 days. In lettuce cultivation, planting time varies according to regions and varieties, but planting is done on tubes or flats. Considering the variety characteristics in planting, the row spacing is adjusted as 30-40 cm and the row spacing is adjusted as 20-30 cm. Mostly, depending on the variety, harvesting is done 60 - 90 days after planting. It is more convenient to harvest lettuce in the morning. The average yield per hectare is 20-40 tons. [Vural et al. 2000, Sevgican 2002)]

According to Turkish Statistical Institute data, total lettuce production in our country in 2021 was determined as 540,569 tons. Lettuce, which is so widely and intensively cultivated, is especially important to benefit from deep learning applications in order to prevent developmental differences that may arise from seedlings by obtaining homogeneous seedlings, to offer healthy seedlings to production at the right time and to minimize seed and seedling losses.

On the basis of previous studies, there are many studies with deep learning for lettuce. Especially for lettuce, studies such as disease detection and product harvest size determination were carried out. (Lu et al., 2019) monitored the growth of lettuce in greenhouses using real-time image and deep learning. They processed the images taken with the imaging system installed in the greenhouse. They developed a mask region-based convolutional neural network (Mask R-CNN) model for simultaneous segmentation. They determined lettuce growth rates according to the values of leaf areas against time. The experimental results showed that the Mask R-CNN model achieved an accuracy of up to 97.63% in predicting the leaf area. The aim of the research conducted by Hassim & Chuah (2020) was to design lettuce variety recognition with at least 90% accuracy using Convolutional Neural Network (CNN) in MATLAB. The CNN was used to classify the seven most commonly found lettuce varieties. The CNN model was trained with 7000 leaves and tested with 1800 leaves to classify the 7 lettuce varieties. Yudha Pratama et al. (2020), used Deep Learning to recognize and detect disease in hydroponic vegetables using Inception V2 algorithm and Faster R-CNN in their research. They divided the training and validation dataset rate into 3 categories. As a result of the study, they determined that the testing and validation rate was affected by deep learning model performances. In another study, Alon (2020) developed a system focusing on lettuce health recognition. With this system, it was determined whether lettuce was healthy or diseased. The system was a machine using deep learning. The machine was connected to a microcontroller raspberry pi 4b. Lettuce health recognition was done with an overall test accuracy of 97.59%. Zhang et al. (2020) suggested a method to monitor the growth of greenhouse lettuce using digital images and a convolutional neural network (CNN). Taking lettuce images as input, they trained a CNN model to learn the relationship between the images and relevant growth-related characteristics, such as leaf fresh weight (LFW), leaf dry weight (LDW), and leaf area (LA). As a result of the experiments, they showed that a CNN with digital images was a robust tool for greenhouse lettuce growth monitoring. Rizkiana et al. (2021) developed a plant growth prediction model using the Artificial Neural Network (ANN) method. The ANN model was tested using different numbers of nodes, from 1 to 7 nodes, daily average temperature, average daily humidity, EC and light intensity input in the hidden layer. Lettuce growth rate prediction was found to be accurate. In another study, Ahsan et al. (2022) used four lettuce varieties grown hydroponically. They took RGB images of lettuce leaves. The results showed that the visual geometry group 16 (VGG16) and VGG19 architectures of the developed DL identified the nutrient levels of the lettuces with 87.5% to 100% accuracy for the four lettuce varieties, respectively.

MATERIAL AND METHODS

Preparation of the Data Set

While preparing the dataset of lettuce vegetable, targeted for object detection and analysis within the project, harvest photos taken in the greenhouses were used. Since lettuce is a vegetable that diversifies as green leaf lettuce and Mediterranean lettuce (lolo rosso), it is possible to see two types of lettuce in the photographs. Many lettuce images taken in the vineyard during harvest and cultivation were collected. Among the images obtained, the images that we could not evaluate within the scope of our project were eliminated. We identified 15 images that would be reliable for our object identification study. In addition, there are 6 * 8 =

48 seedlings in the seedling tabs used in each image. The dataset used in training are shown in Figure 1 and 2.

Data Set Used in Training

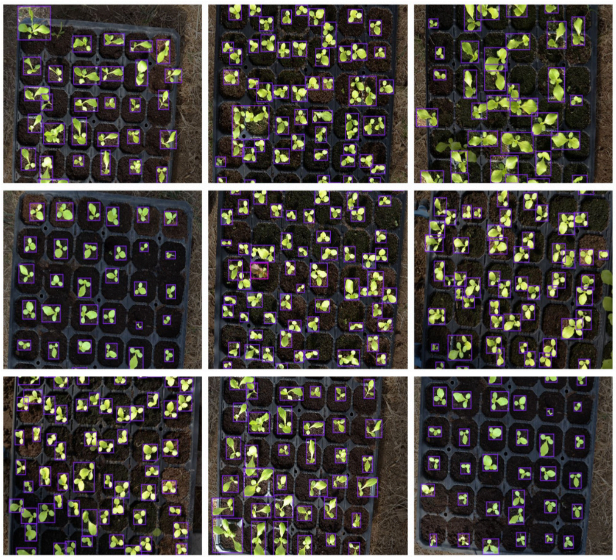


Figure 1. Images from the training sets used during the training of the models (Lettuce)

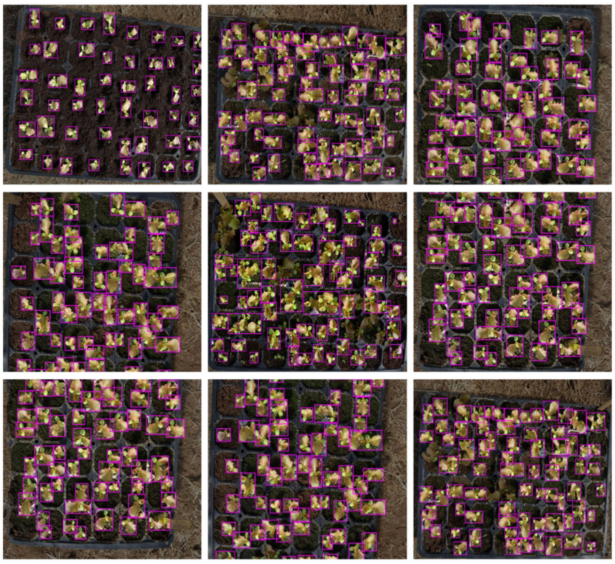


Figure 2. Images from the training sets used during the training of the models (Lolo-Rosso)

Labeling

In order for an object detection model to be able to train on a dataset, the objects targeted to be detected must be labeled/ signed in the dataset to be trained. For this reason, the parts containing the lettuce image in each of the 15 images should be marked with the bounding box area and assigned to the "lettuce seedling" or "lolo-rosso seedling" class, which is the object class it belongs to. There are many programs, websites and utilities available in the open source communities for image labeling. One of these tools is Roboflow, a popular program that is frequently used in object detection projects.

Roboflow is a website that provides all the tools needed to transform raw images into a specially trained computer vision model and distribute it for use in applications, as well as to perform field selections, markings and class labeling on images. This marking and labeling is easily done through the graphical user interface of the website. Figure 3 and Figure 4 show the Label screen.

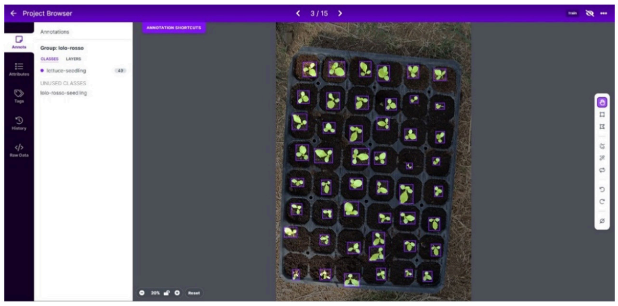


Figure 3. Label Screen (lettuce)

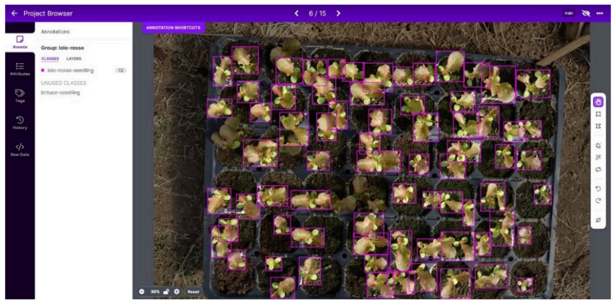


Figure 4. Label Screen (Lolo-Rosso)

Training Model Selection

In the project we carried out, the YOLOv5 family, developed as an open source of the YOLO model family developed by the CNN method, was preferred. The YOLOv5 model of the YOLO model family, which has a significant advantage over models using a two-stage network similar to RCNN, was preferred because it provided advantages in terms of accuracy values and speed ratio to versions developed before it. As explained in detail in the upper sections, the YOLOv5 model also contains models within itself. The YOLOv5n (nano) model was preferred for deep learning training.

Initiation of Training

In order to start the training of the model that will perform lettuce detection, the location of the YOLOv5 model on the computer was visited and a Python runner editor was opened there. The train.py program, which is in the main directory and provides the YOLOv5 training, was checked to be run. The execution of this Python program can be customized with various parameters.

Within the project, the parameters and regulations in the code written below were preferred.

python train.py --img 640 --batch 30 --epochs 400 --data dataset.yaml --weights yolov5n.pt

--img: The pixel size at which the images to be trained will be reduced by the YOLOv5 model. Its default value is 640x640, and it was chosen here in this way.

--batch: The number of data point packets to be used by the display card at a time while training the model.

--epochs: The number of times all training data is shown to the trained network and the weights are updated while training the model.

--data: The path to the .yaml file containing the general path and class information of the file containing the dataset

--weights: The location of the weight file containing the training coefficients to be used in training the model

As a result of running this line of code correctly, the training process of the model has started. The program first checks the YOLOv5 files and checks for any update status. Then, the training process is carried out during the determined number of cycles (epoch).

Performance Matrix

The Performance matrix requires measuring deep learning performance that consists of four core values below:

1) True Positive (TP): There is mature seeding, and the algorithm detects it as mature seeding.

2) False Positive (FP): There is no mature seeding, and the algorithm detects it as no mature seeding.

3) False Negative (FP): There is mature seeding, but the algorithm does not detect it as mature seeding.

4) True Negative (TN): No mature seeding and nothing is detected.

5) Accuracy: Accuracy is a measure that explains that a model or algorithm has been properly trained and can show the results of the training. In this study, accuracy explains how to classify mature seeding. The accuracy is calculated using the following formula:

$$\text{Accuracy} = \frac{(\text{TP+TN})}{(\text{TP+TN+FP+FN})} \quad (1)$$

6) Precision: Shows the ratio of positive predicted cases that are positive. In the context of this study, precision measures a small portion of the object predicted as mature seeding and immature seeding. Accuracy is calculated using the following formula:

$$\text{Precision} = \frac{\text{TP}}{(\text{TP+FP})} \quad (2)$$

7) Recall: This is the ratio between actual positive cases that are predicted to be positive. In the context of this study, recall measures a small portion of seeding that is predicted to be mature. The recall is calculated using the following formula:

$$\text{Recall} = \frac{\text{TP}}{(\text{TP+FN})} \quad (3)$$

8) F1 Score: Also known as an F-score or F-measure counterweight. F1 scores are a measure of model accuracy that combines precision and recall. In the context of this study, a good F1 score indicates that there are fewer false positives and false negatives. This shows that this model correctly identifies mature seeding from the existing dataset. The model or algorithm is considered perfect if the F1 score is 1. F1 scores are calculated using the following formula:

$$\text{F1} = \left(\frac{\text{2xPrecisionxRecall}}{\text{Precision+Recall}}\right) \quad (4)$$

9) Training time: Training time is a metric used in this research to measure the time needed to conduct training on the modeling algorithm chosen for the dataset.

10) Detection Speed: Speed is a metric used in this study to measure the time required by the algorithm to process and detect seeding objects.

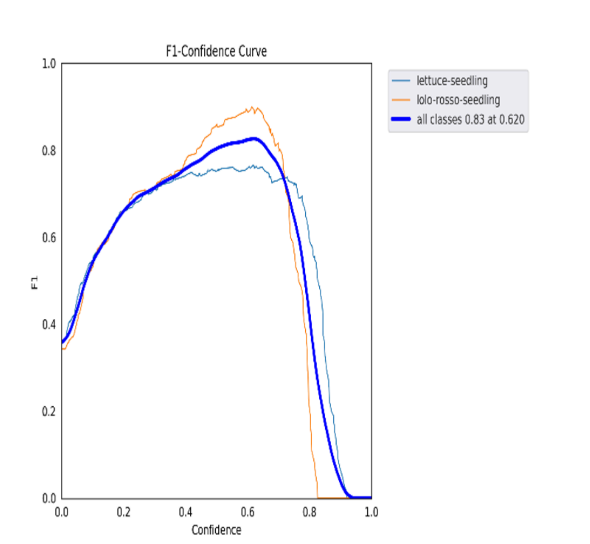
RESULT FINDINGS

Analyzing the results of YOLOv5 algorithms according to error matrix metrics

F1 Score

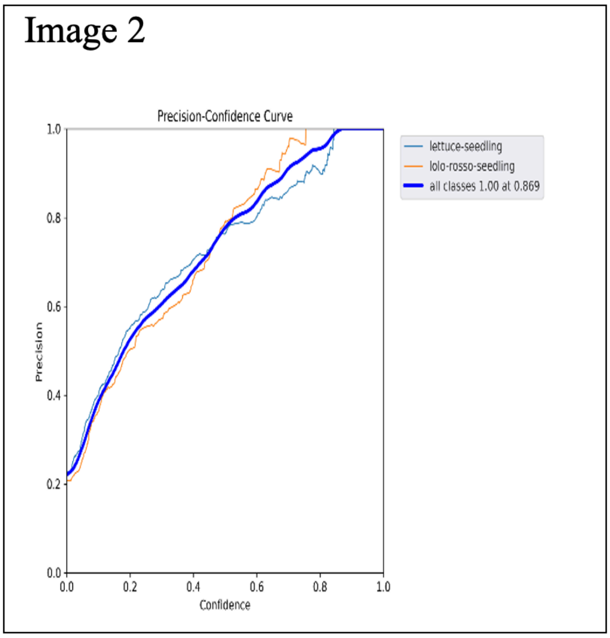
Image 1: Size: 640x640, Batch: 30, Epoch: 400, Algorithm: YOLOv5n

Image 1



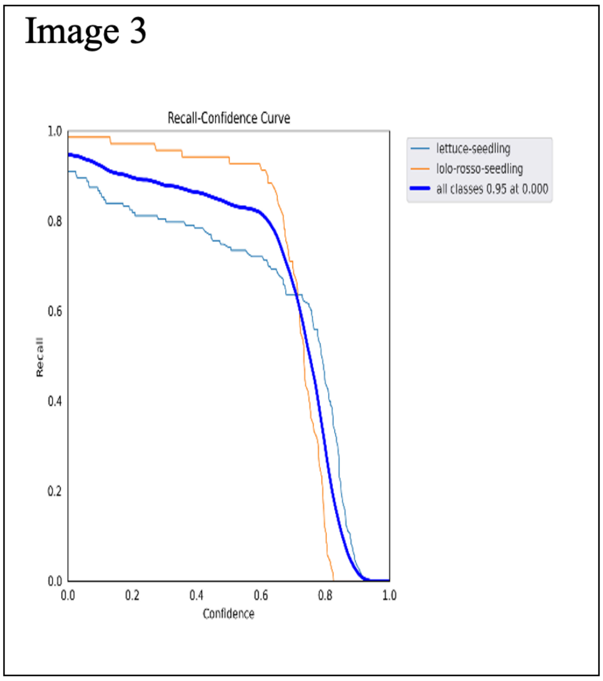
Precision

Image 2: Size: 640x640, Batch: 30, Epoch: 400, Algorithm: YOLOv5n



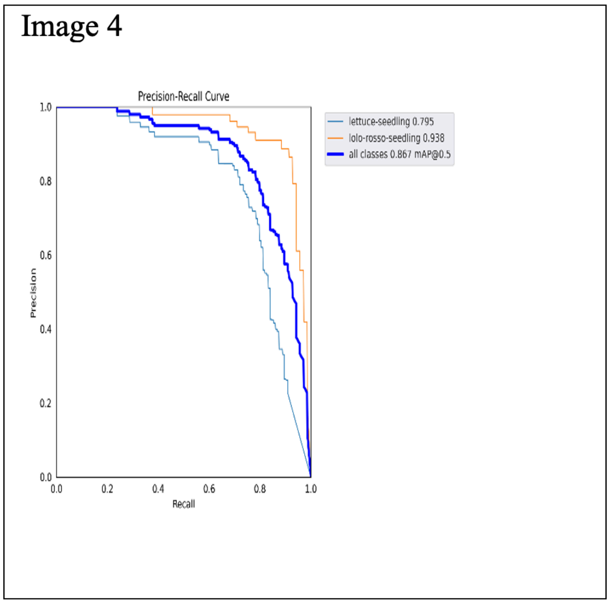
Recall

Image 3: Size: 640x640, Batch: 30, Epoch: 400, Algorithm: YOLOv5n



Precision Recall

Image 4: Size: 640x640, Batch: 30, Epoch: 400, Algorithm: YOLOv5n



Loss Function

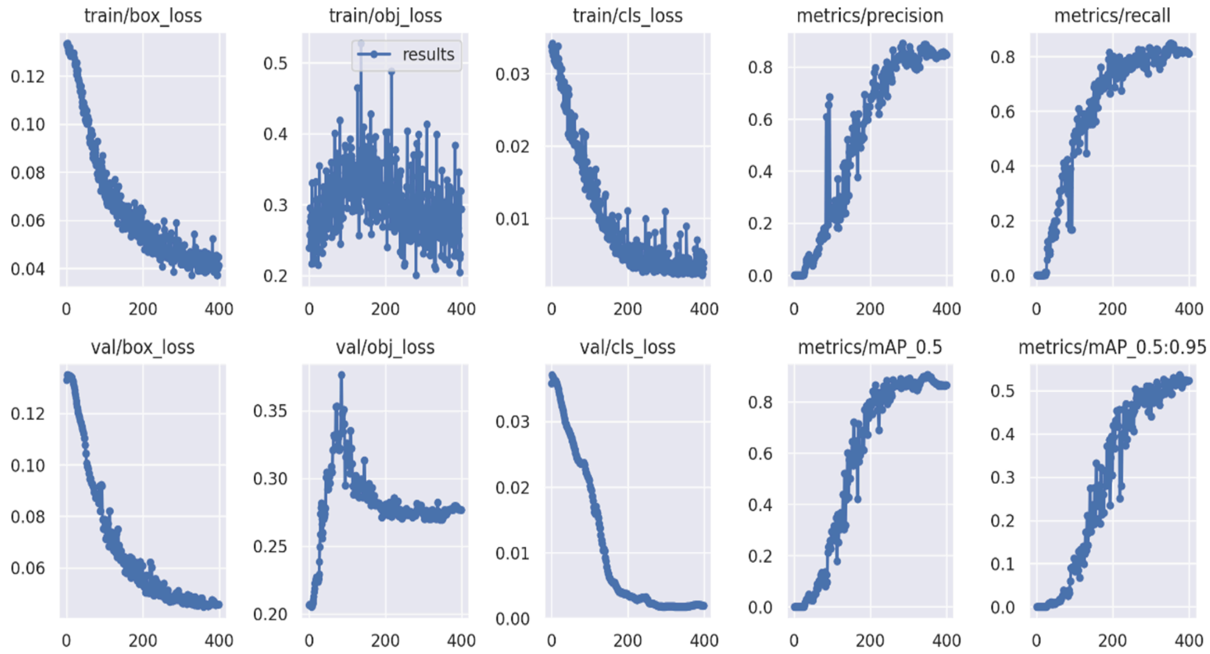
Image 5: Size: 640x640, Batch: 30, Epoch: 400, Algorithm: YOLOv5n

TRAINING RESULT

Figure 5. "Validation Batch" prediction markings resulting from the training of the models (Lettuce-Seeding)

Figure 6. "Validation Batch" prediction markings resulting from the training of the models (Lolo-Rosso Seeding)

Image 5



Configuration Files and Parameters

These algorithms use the following configuration files which are available under the yolov5 framework and contain the hyper parameters used to train the models:

Descriptions of the parameter columns in the table: “Model” : Full name of the corresponding YOLOv5 algorithm model

“size” : The size of the model’s input image, in pixels

“mAP^{val}” : The mean average precision value of the

YOLOv5 model uses the configuration file “hyp.scratch-low.yaml” and the hyperparameters in it.	lr0: 0.01 lrf: 0.01 momentum: 0.937 weight_decay: 0.0005 warmup_epochs: 3.0 warmup_momentum: 0.8 warmup_bias_lr: 0.1 box: 0.05 cls: 0.5 cls_pw: 1.0 obj: 1.0 obj_pw: 1.0 iou_t: 0.20 anchor_t: 4.0 fl_gamma: 0.0 hsv_h: 0.015 hsv_s: 0.7 hsv_v: 0.4 degrees: 0.0 translate: 0.1 scale: 0.5 shear: 0.0 perspective: 0.0 flipud: 0.0 fliplr: 0.5 mosaic: 1.0 mixup: 0.0 copy_paste: 0.0	YOLOv5 model uses the configuration file “hyp.scratch-high.yaml” and the hyperparameters in it.	lr0: 0.01 lrf: 0.1 momentum: 0.937 weight_decay: 0.0005 warmup_epochs: 3.0 warmup_momentum: 0.8 warmup_bias_lr: 0.1 box: 0.05 cls: 0.3 cls_pw: 1.0 obj: 0.7 obj_pw: 1.0 iou_t: 0.20 anchor_t: 4.0 fl_gamma: 0.0 hsv_h: 0.015 hsv_s: 0.7 hsv_v: 0.4 degrees: 0.0 translate: 0.1 scale: 0.9 shear: 0.0 perspective: 0.0 flipud: 0.0 fliplr: 0.5 mosaic: 1.0 mixup: 0.1 copy_paste: 0.1

model. This value is a metric showing the performance of the model to recognize an object and is expressed as a percentage. mAP^{val}50-95 gives an average performance value for all targets between 50% and 95%. mAP^{val}50 shows the performance of the model by considering only the best match.

"Speed" : Parameter columns that specify the processing speed of the model in ms. This value indicates how long the model can process for an input image. The CPU b1 column shows the processing speed of the model using a CPU processor, while the V100 b1 and V100 b32 columns show the single and 32-core processing speed of the model using the NVIDIA V100 graphics processor.

"Params" : Shows the total number of weight parameters of the model in M (Million).

"FLOPs" : FLOPs, short for "FLoating point OPerations", indicates the number of processes the model will perform for an input image (640x640 by default) in B (Billion).

CONCLUSION

In our study,object detection accuracies in the sample training and validation images performed with the YOLOv5 Nano model and the prepared dataset were examined. When the metric data and accuracy prediction rates indicating the object detection success of the models was examined, it was confirmed that the training result of the model was successful. In a similar study (Du et al., 2020), they found that the F1 score value was 97.65% in the system of determining the maturity of lettuce with deep learning. They found that the product certainty detection value was 99.82%. In another study (Yudha Pratama et al., 2020), they found Accuracy 70%; Precision 97%; Recall 68% and F1 Score 80% in the use of deep learning medtod to recognize and detect disease in hydroponic vegetables using Inception V2 algorithm and Faster R-CNN. They measured the learning speed as 0.0002 for all data. In this study, as a result of the training, F1 score was 83%; Precision 100%; Recall 95%; Precision Recall 86.7%. The learning rate for all given pictures was found to be 0.0005. When the results of previous studies are compared with the results of our research, it is seen that similar results are obtained. However, it should be considered that these results may change when working on datasets of different sizes and diversity, or when changes are made on the hyper parameters and general operating parameters related to the training algorithms, or when a success rating based on speed performance rather than object detection success is made.

COMPLIANCE WITH ETHICAL STANDARDS

Conflict of interest

The authors declared that for this research article, they have no actual, potential or perceived conflict of interest.

Author contribution

The contributions of the authors to the present study is equal. The authors read and approved the final manuscript. The authors verify that the Text, Figures and Tables are original and that they have not been published before.

Ethical approval

Ethics committee approval is not required.

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Data availability

All data associated with this research were indicated and used in the manuscript submitted.

Consent for publication

All authors consented to the publication of this manuscript.

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