

YOLOv5 Model Application in Real-Time Robotic Eggplant Harvesting

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Abstract

Deep learning studies in agricultural automation have accelerated in recent years due to its benefits such as increasing product efficiency and reducing labor force. Deep learning is a powerful tool for automation in agriculture with applications ranging from disease identification and crop yield detection to fruit ripeness classification. It helps to automate various processes in agriculture and to perform time-consuming tasks in a shorter time. It quickly processes the data required for robotic harvesting systems and makes it available to the system. In this study, a machine learning study was carried out to be used in the robotic harvesting of eggplant fruit, which is a product that can take time to select and collect in the agricultural area where it is cultivated. YOLOv5 (nano-small-medium and large models) was used for the deep learning method. All training and test metric values of the models were analyzed. It was determined that the most successful model was the model trained with YOLOv5m algorithm on images of 640×640 size with 12 Batches and 110 Epochs. The results of the model values were analyzed as “metrics/precision”, “metrics/recall”, “metrics/mAP_0.5” and “metrics/mAP_0.5:0.95”. These are key metrics that measure the detection success of a model and indicate the performance of the relevant model on the verification dataset. It was determined that the metric data of the “YOLOv5 medium” model was higher compared to other models. The YOLOv5m model gave the highest score with F1 score of 85.66%, precision of 95.65%, recall of 96.15%, and mAP at 0.5:0.65 of 78.80%. Hence, it was understood that “Model 3” was the best detection model to be used in robotic eggplant harvesting to separate the eggplant from branch.

Keywords: deep learning, eggplants, classification, YOLOv5

1. Introduction

Deep learning is a subfield of artificial intelligence that focuses on the development of neural networks and deep neural architectures to solve complex tasks. This method aims to process and learn data using mathematical model-based systems called artificial neural networks. It has the ability to learn based on large amounts of data and can be used to solve complex problems (Çetiner et al., 2022). It is stated that artificial neural networks consist of multi-layered structures. Each layer of this multi-layered structure can learn features at successive levels by processing input data. Each layer learns more abstract and higher-level features than the previous one. They are called “deep” because they have multiple hidden layers between the input and output layers. Each layer in a deep neural network enables the model to learn complex patterns and representations by incrementally extracting higher-level features from the input data. Deep learning can model complex relationships in data sets by means of the multi-layered structure of artificial neural networks. Each layer of this multilayer structure increases the representation power by transforming the input data into higher-level features. Thus, deep learning models can automatically learn more complex and abstract features and recognize patterns in data sets (Aktaş, 2022).

Deep learning is widely used in various fields and applications. One of the important areas where deep learning is used is medical imaging. It is used in medical imaging, especially MRI analysis. These methods show promise in improving clinical applications and have been applied in tasks such as image segmentation, disease classification, and anomaly detection (Lundervold et al., 2019). Another area where deep learning finds wide application is the automation of industries. Ayadi et al. (2022) emphasized the use of deep learning-based soft sensors to increase automation flexibility in industries. Furthermore, deep learning is used in the field of artificial intelligence, especially in natural language processing (NLP). Deep learning models such as repetitive neural networks (RNNs) and convertors have been successful in tasks such as machine translation, sentiment analysis and text generation. These models have revolutionized the field of NLP by capturing complex linguistic patterns and semantic relationships. Deep learning has made significant contributions to computer vision. Convolutional neural networks (CNNs), a type of deep learning model, have achieved remarkable results in tasks such as object detection, image classification, and face recognition. CNNs enable accurate and efficient analysis of images and videos by automatically learning hierarchical representations of visual data (LeCun et al., 2015).

Deep learning is used in many applications in agriculture. One of the most common applications is the detection of diseases and pests in plants. Deep learning models have been used to develop image recognition systems that can identify diseases and pests in crops based on leaf or plant images (Zhang et al., 2020; Liu et al., 2020). These models can help farmers detect and diagnose plant diseases early, enabling timely intervention and preventing crop losses. Another application of deep learning in agriculture is precision agriculture. By analyzing data from various sources such as satellite imagery, weather data and soil sensors, deep learning models can provide insights and recommendations to optimize crop management practices. This includes tasks such as crop prediction, irrigation scheduling and nutrient management (Ampatzidis, 2018; Jin et al., 2020). Deep learning is also used to increase the efficiency of agricultural operations. It can be used for weed detection and classification, thus, targeted and precise weed control precautions can be taken (Cicco et al., 2017). Another use of deep learning in agriculture is classification. Models have been used for automatic fruit and vegetable classification, allowing faster and more accurate classification according to quality and ripeness (Aji et al., 2019). Deep learning models can enable robots and drones to perform tasks such as autonomous harvesting, crop monitoring, and autonomous spraying (Ampatzidis et al., 2017). These technologies can increase productivity, reduce labor costs and minimize the use of agricultural chemicals. Deep learning is not only used in precision agriculture applications. It has also found a place in livestock management. By analyzing data from sensors and cameras to monitor animal behavior, health, and welfare, it can help farmers detect abnormalities, predict disease outbreaks, and optimize feeding and rearing practices (Umar et al., 2022). In general, deep learning has the potential to revolutionize agriculture by enabling data-driven decision-making, increasing efficiency and reducing environmental impact. However, successful application of deep learning in agriculture requires handling challenges such as data collection and processing, model interpretability, and ethical issues (Dara et al., 2022; Ryo et al., 2022). Eggplant is a vegetable that is widely grown in the world and in almost every region of our country. It is a plant that has a significant share not only as a summer vegetable but also in greenhouse cultivation in our country. Correctly determining the harvesting time of eggplant, one of the important vegetables of Turkish cuisine, will provide ease of marketing and will also affect its shelf life. In this context, determining the harvesting time of eggplant correctly and harvesting at the right time is one of the important parameters.

2. Material and Method

2.1 Material

Eggplant belongs to the Solanaceae family and its homeland is known to be India-Burma and Assam. When vegetable cultivation in the world and Turkey is considered, eggplant (*Solanum melongena* L.) is among the most produced, consumed and economically high species (Eşiyok, 2012). Eggplant is rich in vitamins, minerals, has a high antioxidant capacity and is rich in phenolic acids. It is called 'egg-plant' because its fruit shape and color look like an egg (Sao et al., 2010). The fruit shape, fruit color, and fruit size show a very large variation in eggplants. Eggplant fruit forms are long, medium long and round. There is a big difference between the harvesting size and the size of the fruit whose seeds have ripened. When a fruit that has reached harvesting ripening is left as a seed, it reaches 4-6 times the harvest size and weight (Uzun et al., 2000, Vural et al., 2000). The harvesting process of eggplant involves several aspects that will affect fruit quality and yield. Researches have shown that the fruit ripening stage at harvesting time also affects fruit quality (Passam et al., 2010). The harvesting criteria of eggplant are affected by several factors such as harvest season, fruit ripeness and environmental conditions. It is known that the harvest season is related to the amount of phenolic acid in eggplant, indicating that harvest timing may affect the nutritional quality of the fruit (Gürbüz et al., 2018). In addition to the developmental stage of the plant and harvest time, fruit type, shape and size are also important

items in determining the optimum harvest time (Ferreira-Santos et al., 2021). In African eggplant, it is recommended to harvest the fruits before the skin hardens and the original variety color changes. This period is generally estimated at 70-90 days from the date of planting, depending on varieties and weather conditions (Msogoya et al., 2014). The harvesting method of eggplant is very important. Eggplants are typically handpicked at the appropriate stage of ripening (Xu et al., 2020). In terms of the physiological quality of eggplant seeds, it has been observed that the position of the fruit on the plant and the time of harvest may affect the seed quality, and the importance of considering these factors during the harvesting process has been emphasized (Reis et al., 2012). The limited shelf life of eggplant after harvesting requires careful post-harvest handling to maintain its quality (Santacatalina et al., 2016).

2.2 Method

2.2.1 Labeling

Labeling in deep learning is the process of assigning images in the data set to the correct classes. This process increases the training and classification performance of deep learning models. In order to train an object detection model on a dataset, the objects targeted to be detected must first be labeled in the dataset to be trained. For this reason, the parts containing the eggplant image in each of the 52 planting images taken from producer greenhouses in Tekirdağ Naip Village were marked with a bounding box area. Examples of images are shown in Figure 1.



Figure 1. Samples of images taken from producer greenhouses in Tekirdağ Naip Village

After the markings were made, it was assigned to the “eggplant” class, which is the object class it belongs to. The labeling process was performed on Roboflow, a popular website frequently used in object detection projects. Roboflow is a web platform designed to simplify and accelerate the data preparation and model training phases of image-based artificial intelligence projects. This marking and labeling process is easily done through the graphical user interface of the website. Within the scope of the study, the YOLO deep learning model was selected for the model to be used. When the text file of any image containing the labeled object classes is entered, the class information and coordinate information of the marking and labeling will be listed. Label screen is shown in Figure 2.

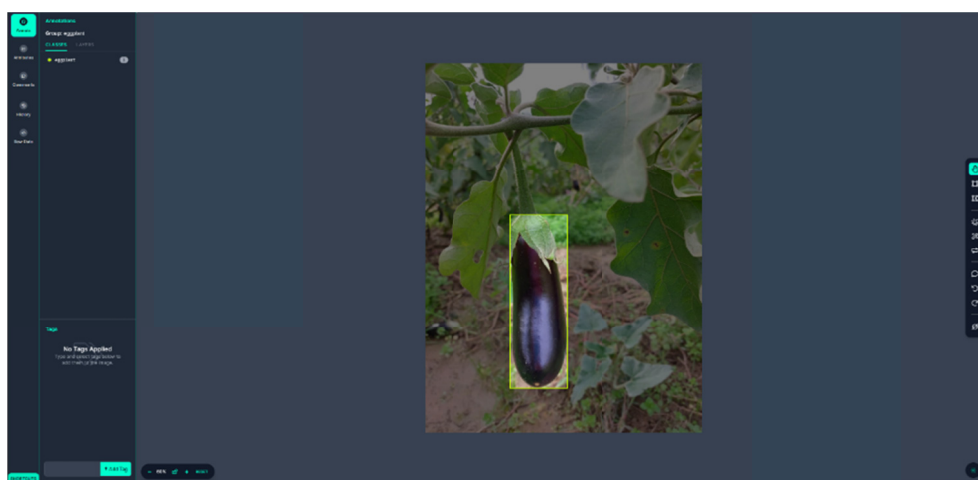


Figure 2. Labeling screen

2.2.2 Training Model Selection

In the study we carried out, the YOLOv5 family, developed as an open source of the YOLO model family developed by the CNN method, was preferred. YOLOv5 deep learning model is an object detection algorithm that has been widely studied and developed in various fields. It also has high detection speed and sensitivity (Li et al., 2023). YOLOv5 is one of the versions of the YOLO (You Only Look Once) algorithm, a popular object detection algorithm in computer vision. It is considered a lightweight version compared to the previous versions and uses the PyTorch framework instead of the Darknet framework (Liu et al., 2022). YOLOv5 is known for its fast detection speed and high accuracy (Sozzi et al., 2022). Due to this feature, YOLOv5 deep learning model is used in many fields. In fabric defect detection, Shi et al. (2022) improved the detection accuracy of small target objects by adding a layer of ultra-small detection heads to YOLOv5s. In the context of autonomous landing point detection on defective UAVs, Nepal et al. (2022) compared the accuracy and speed of YOLOv3, YOLOv4, and YOLOv5l and found that YOLOv5l had the best performance. YOLOv5 was also used in other fields such as agriculture and remote sensing. Batin et al. (2023) proposed an improved YOLOv5 method to detect wheat ears in UAV images and detected false ears caused by occlusion conditions. Zhao et al. (2021) developed a wheat ear detection method based on improved YOLOv5 and indicated its efficiency in UAV images. In the field of agriculture, YOLOv5 was used for automatic cluster detection in white grape varieties, and rapid detection with the same accuracy as YOLOv4 was achieved (Sozzi et al., 2022). In precision agriculture, YOLOv5 was used in a robotic sprayer system for real-time tobacco recognition and spraying, and its efficiency in detecting and targeting specific objects was indicated (Nasir et al., 2023). Xue et al. (2022) used a YOLOv5 network developed for ground object recognition in remote sensing images and evaluated the detection effect using performance indicators such as precision, recall and mAP. Another use of YOLOv5 is in medicine. In the medical field, Tsai (2023) graded AB-YOLOv5 and PB-YOLOv5 for rib fracture detection in chest X-ray images and indicated the efficiency of YOLOv5 in this application. The research conducted by Carvalho et al. (2022) can be given as an example of another usage area. In their study, they emphasized that the YOLOv5 architecture had better performance in intelligent defect detection in asphalt pavements. Kumar et al. (2023) used the YOLOv5 detection network for robust vehicle detection and obtained significant results on benchmark datasets. The accuracy of YOLOv5 was also been evaluated in the context of cyber-attacks on the Internet. Zhang et al. (2022) tested the impact of various cyber-attacks such as L-BFGS, FGSM, C&W, BIM, PGD, One Pixel Attack, and Universal Adversarial Perturbations on the accuracy of YOLOv5. In general, YOLOv5 is a versatile object detection algorithm that has been developed and applied in various fields and has shown promising results in terms of accuracy and precision. Its speed and detection performance make it a popular choice for many applications. In the study, YOLOv5n/s/m and l (nano-small-medium and large) models were preferred for deep learning training.

2.2.3 Initiation of Training

To start training the model that will detect the eggplant on the seedling, the next step after running the YOLOv5 model on the computer is to open the Python executable editor. After opening the editor, the train.py program,

which is in the main directory and provides the YOLOv5 training, was run. The last step is to run the Python program and customize it with parameters values.

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

```
python train.py --img 640 --batch 12 --epochs 110 --data dataset.yaml --weights yolov5n.pt
python train.py --img 640 --batch 12 --epochs 110 --data dataset.yaml --weights yolov5s.pt
python train.py --img 640 --batch 12 --epochs 110 --data dataset.yaml --weights yolov5m.pt
python train.py --img 640 --batch 12 --epochs 110 --data dataset.yaml --weights yolov5l.pt
```

--img: The pixel size at which the images to be trained will be reduced by the YOLOv5 model. Its default value is 640×640 , 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.

By running these lines of code, the training process of the model was started. The program first checks the YOLOv5 files. The training process is carried out during the determined number of cycles (epoch).

2.2.4 Evaluation Indicators

True Positive (TP) indicates the number of positive images that are correctly categorized as positive.

True Negative (TN) indicates a specific sample number that the model correctly identified a negative sample as actually negative.

False Positive (FP) details the number of samples that a negative sample was incorrectly identified as a positive sample by the algorithm.

False Negatives (FN) indicates the number of samples that the algorithm incorrectly categorized a positive sample as negative.

➤ Accuracy: This metric is used when the classification problem has a balanced class distribution (similar amount of data in each class). If the class distribution is unbalanced, the problem of capturing the class with a low number of classes may be encountered.

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

➤ Error Rate: It is the rate of frequency of incorrect classifications/predictions in the problem.

$$\text{Error Rate} = \frac{\text{FN} + \text{FP}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \text{ or } (1 - \text{Accuracy}) \quad (2)$$

➤ Precision: It is the success rate of positive class (1) predictions. It indicates how many of the predicted positive classes (classes predicted as 1) are actually positive.

$$\text{Precision} = \frac{\text{TP}}{\text{FP} + \text{TP}} \quad (3)$$

➤ Recall: It is the correct prediction rate of the positive class (1). It is the metric value that shows how many of the predicted positive classes have been predicted correctly.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (4)$$

➤ F1-Score: It is the harmonic average of precision and recall values. It retains the effect of both Precision and Recall values.

$$\text{F1 Score} = \frac{2 \times \text{Precision}}{\text{Precision} + \text{Recall}} \quad (5)$$

➤ Mean Average Precision: This metric is the precision and recall product of detected bounding boxes. The MAP value scale varies between 0 and 1. The higher the value, the better the result. MAP is found by calculating

the average precision (AP) for each class separately and then calculating the average over the class. The result is accepted as true positive if the mAP value is above 0.5.

$$mAP = \frac{1}{C} + \sum_{k=1}^T P(k) \Delta R(k) \quad (6)$$

3. Research Results

F1 Score, Precision and Recall value graphs were examined according to the error matrix metrics of YOLOv5 algorithms. F1 Score, precision, recall and loss function graphs are given in Figures 3, 4, 5 and 6, respectively.

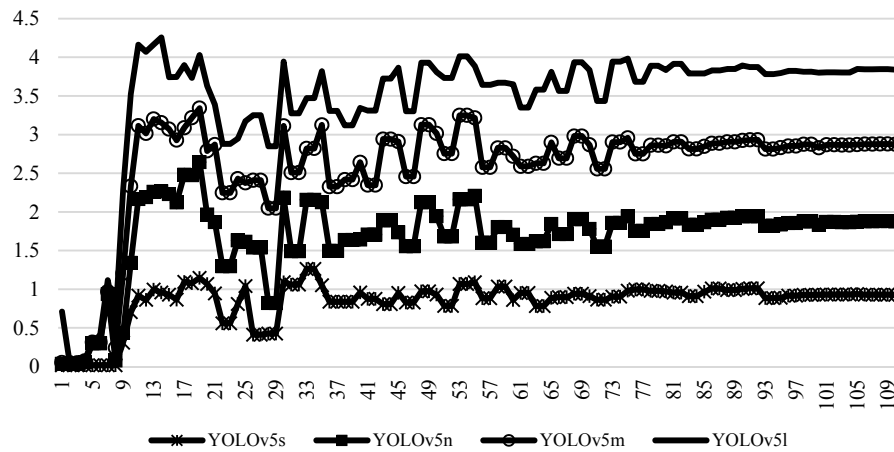


Figure 3. F1 Score graph

Model 3: When the graph was examined, it was seen that the model showed a general increasing trend over time. The F1 score is the harmonic average of the precision and recall metrics and is an indicator of overall performance. The increasing trend indicated that the overall performance of Model 3 improved.

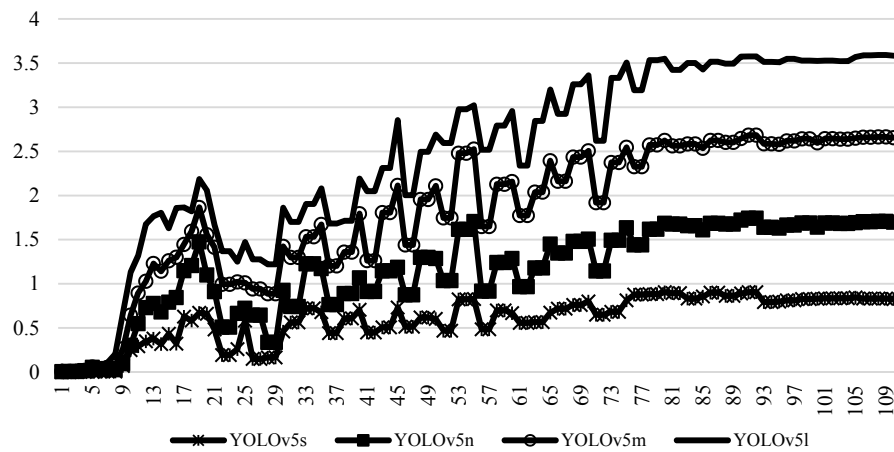


Figure 4. Precision graph

Model 3: The Precision graph indicated that the model generally exhibited a high precision score and this score showed a slight increasing trend over time. Besides, the graph indicated that most of the positive predictions of Model 3 were correct.

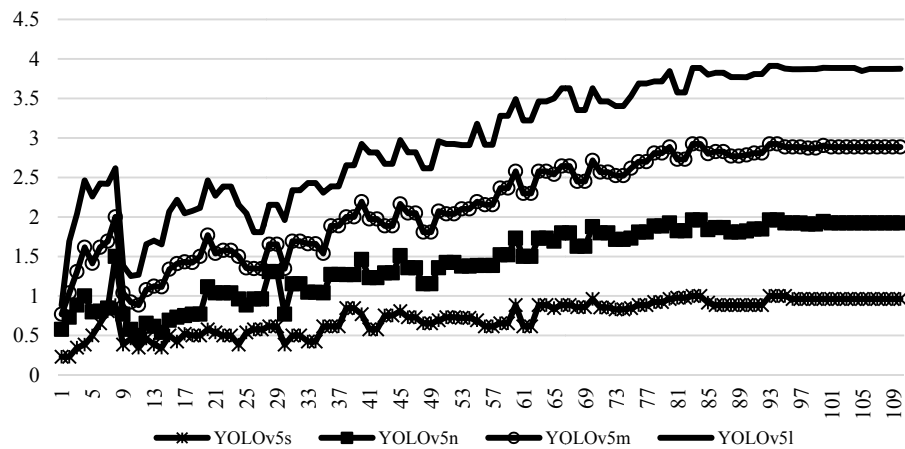
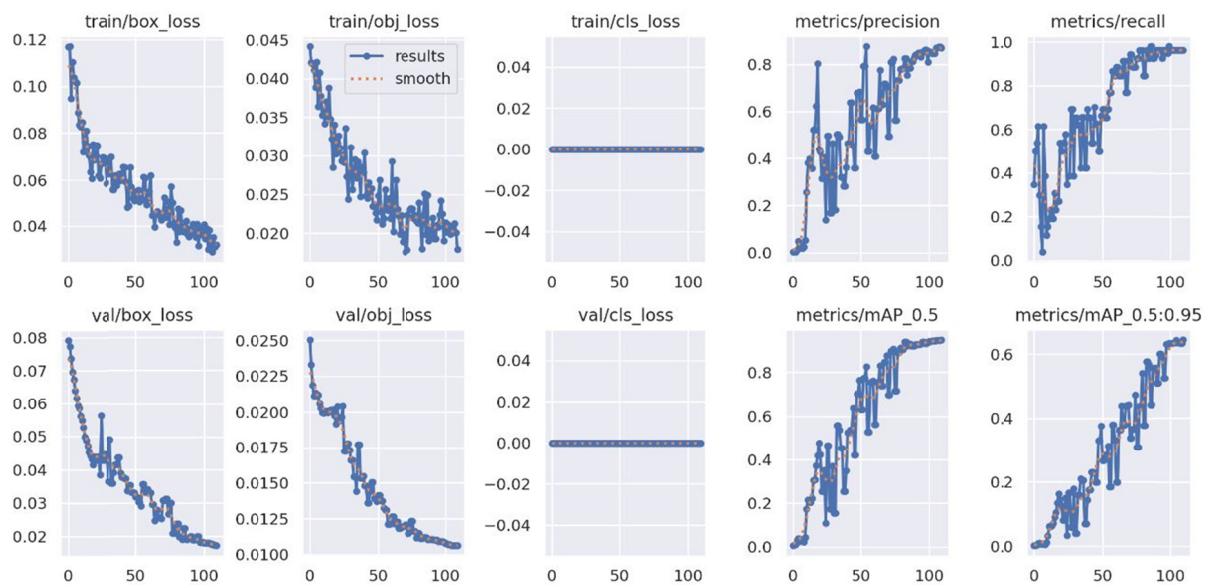
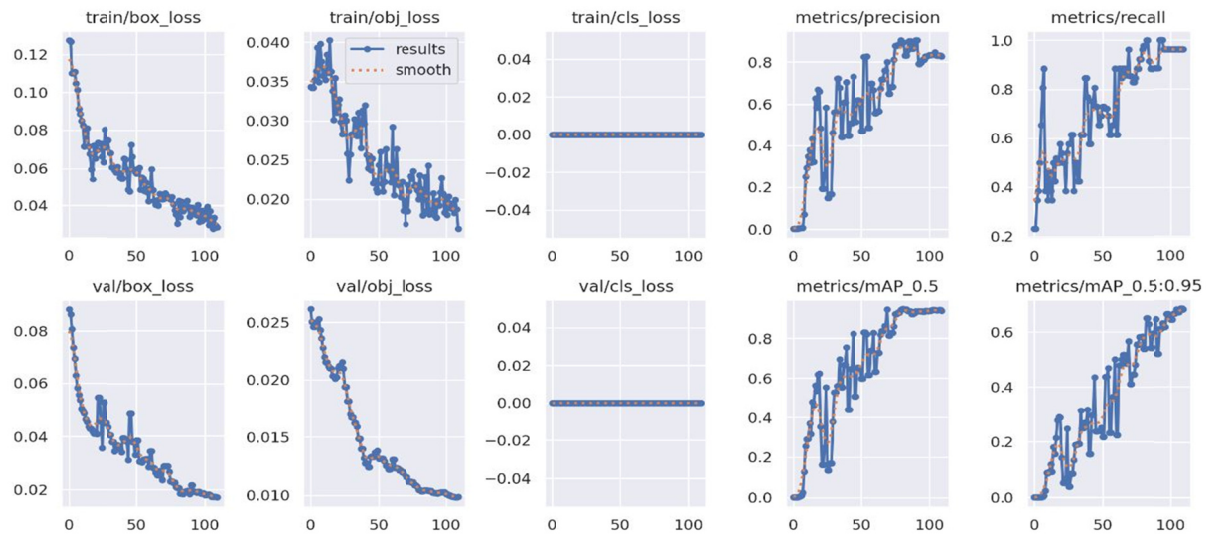


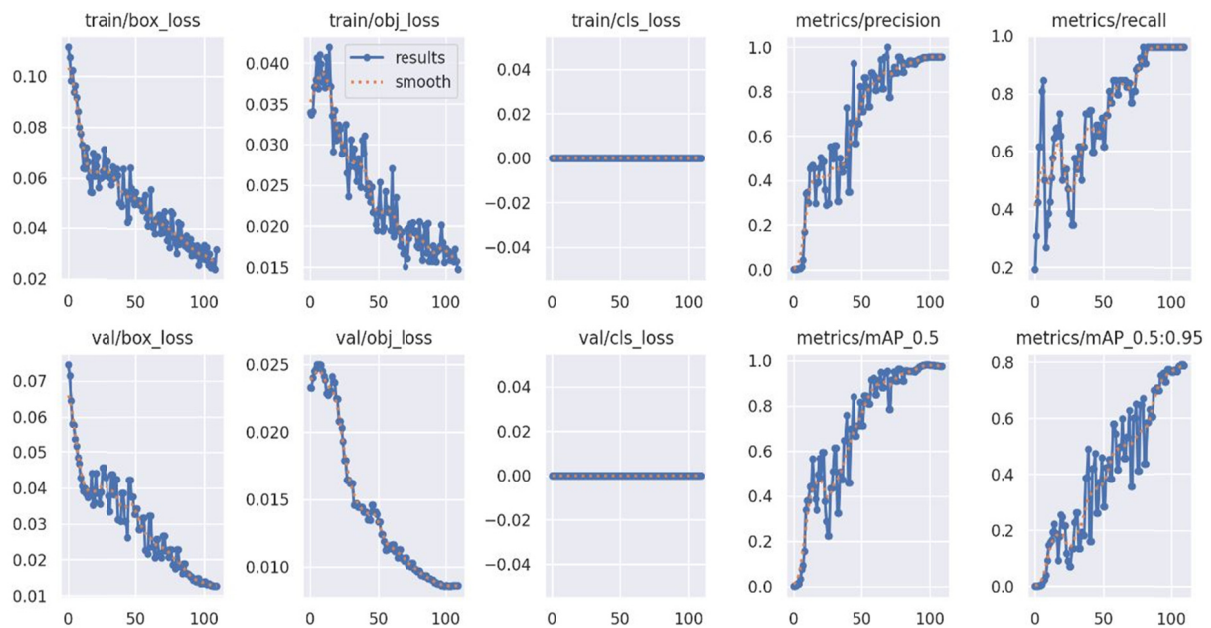
Figure 5. Recall graph

It can be observed that the model constantly improved and was able to make more correct positive classifications over time. It meant that the development and adjustment of the Model 3 proceeded accurately. However, the fact that the graph still contained some fluctuations indicated that there was variability in the model's performance in certain situations or when encountered with certain data subsets.

(A) Size: 640×640 , Batch: 12, Epoch: 110, Algorithm: YOLOv5n



(B) Size: 640×640 , Batch: 12, Epoch: 110, Algorithm: YOLOv5s



(C) Size: 640×640 , Batch: 12, Epoch: 110, Algorithm: YOLOv5m

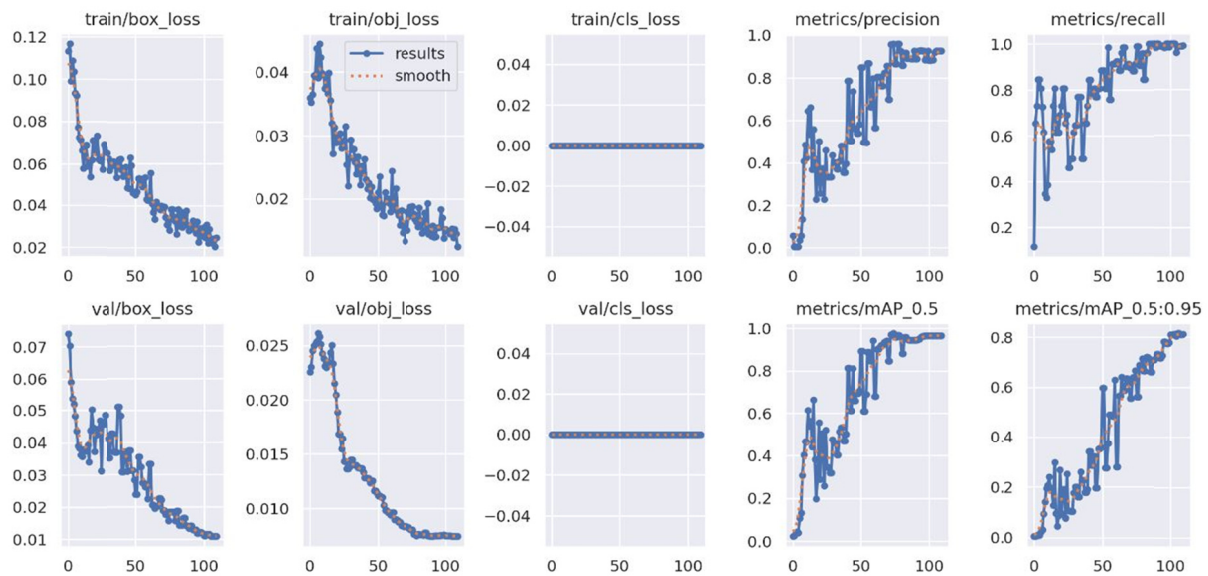
(D) Size: 640×640 , Batch: 12, Epoch: 110, Algorithm: YOLOv5l

Figure 6. Loss Function graph

It was seen that Model 3 errors generally decreased over time. This meant that the model generally got better during the training process and its predictions were closer to the true values.

COMPARISON OF MODEL ALGORITHMS:

The metric data of Model “3” and the difference of other models to these data are given in Table 1.

Table 1. Comparison of model algorithms

Model	Metrics/mAP_0.5	Difference (Model 3)	Metrics/mAP_0.5:0.95	Difference (Model 3)
Model 3	0.97545		0.78802	
Model 2	0.93961	0.03584	0.68131	0.10671
Model 1	0.9483	0.02715	0.64466	0.14336
Model 4	0.96631	0.00914	0.81199	-0.02397
Model	Train/box_loss	Difference (Model 3)	Train/obj_loss	Difference (Model 3)
Model 3	0.031798		0.014735	
Model 2	0.028442	0.003356	0.016246	-0.001511
Model 1	0.31967	-0.000169	0.017904	-0.003169
Model 4	0.024745	0.07053	0.012433	0.002302
Model	val/box_loss	Difference (Model 3)	val/obj_loss	Difference (Model 3)
Model 3	0.012554		0.0086365	
Model 2	0.017055	-0.004501	0.0098648	-0.0012283
Model 1	0.017151	-0.004597	0.01639	-0.0020025
Model 4	0.010914	0.00164	0.0074921	0.001144

According to the result values in Table 1,

-YOLOv5m: Medium model achieved the highest score of mAP_0.5:0.95, which is a good overall indicator of the model’s performance as it averages the model’s sensitivity at various IoU thresholds. The 0.5 mAP_0.95 result was found as 0.78802. Precision and recall values were also high for this model.

-YOLOv5s: The Small model came second with a mAP_0.5: 0.95 value of 0.68131, precision value of 0.82769 and recall value of 0.96154.

-YOLOv5n: The Nano model had a mAP_{0.5:0.95} value of 0.64466, precision value of 0.87029 and recall value of 0.96154.

-YOLOv5l: The Large model showed the lowest performance with a mAP_{0.5:0.95} value of 0.81199, precision value of 0.92794 and recall value of 0.99081.

However, these rankings may vary depending on the specific use case. If recall is prioritized over precision in our application, the ranking will change. Train/cls_loss and val/cls_loss parameters, which express the classification losses in training and validation data, play an important role in models that require the detection of many object classes. When the train/box_loss, train/obj_loss, val/box_loss, val/obj_loss values in Table 1 were examined, it was seen that the model with the least loss values in the training set was “Model 4”. However, it was seen that the model with the least loss values in box_loss and val_loss in the validation data was “Model 3”.

3.1 Training Result

Training result screenshots are shown in Figure 7.

Size: 640 × 640, Batch: 12, Epoch:
110, Algorithm: YOLOv5n



Size: 640 × 640, Batch: 12, Epoch:
110, Algorithm: YOLOv5s



Size: 640×640 , Batch: 12, Epoch:
110, Algorithm: YOLOv5m



Size: 640×640 , Batch: 12, Epoch:
110, Algorithm: YOLOv5l



Figure 7. Validation Batch” prediction markings resulting from the training of the models

4. Discussion

Deep learning is used especially in classification and discrimination in agricultural systems. High accuracy and productivity are achieved in the processes of identifying and harvesting agricultural products. Increasing yield due to this productivity contributes to the development of selective harvesting systems. Hidayah et al. (2022) used tomatoes, potatoes, eggplants and peppers in their study on disease detection with deep learning on 4 groups of products. They trained a dataset consisting of a total of 16580 images with 100 epochs and 16 batch sizes. As a result of the comparison of deep learning models, they emphasized that they found the best result in the YOLOv5 model. They found the average precision of the YOLOv5 model as 94.2%. Haque et al. (2022) used various models of deep learning in their disease detection system for eggplant. The deep learning models were VGG16, Inception V3, VGG 19, MobileNet, NasNetMobile and ResNet50. They created the training set from 9 disease types for eggplant. According to the test set results, they emphasized that they achieved a success rate close to 99%. Hu et al. (2023) chose the YOLOv5 deep learning model as the method in their study in which they used pepper, eggplant and tomato as materials for the detection of seedling branch nodes. As a result of the study, they found that the average sensitivity value was 95% and the detection speed was 0.019 sec. Wang et al. (2023) carried out a classification and identification study for potatoes with YOLOv3 deep learning method. Phan et al. (2023) used YOLOv5 and CNN deep learning model to classify tomatoes. As a result of the experiments performed with 200 epochs, batch 128 and image size of 224×224 for the training set, they determined the rate of finding damaged tomatoes as 94% for YOLOv5m. Sa et al. (2023) used the R-CNN model in their fruit detection system studies using the deep learning model. Rahnemoonfar et al. (2023) predicted the number of cherry tomatoes on the branch with 93% accuracy with deep learning model. Wang et al. (2019) conducted experiments using YOLO as a training model in their study of counting mango fruit on trees. Lee et al. (2022) used YOLOv2 and YOLOv3 models in their harvest prediction system study based on the flowering period for tomatoes. Liu et al (2022) used the DA-Mask RCNN deep learning model in their automatic asparagus harvesting system study and determined the precision, recall and F1-score values as 0.993, 0.971 and 0.982, respectively. According to these values, they confirmed the suitability of the model. Abeyrathna et al. (2023)

examined which deep learning model was suitable for robotic harvesting systems. The compared models were YOLOv4, YOLOv5 and YOLOv7 deep learning models. They emphasized that the models to be used in such systems were YOLOv5 and YOLOv7. In the modeling study, the best model for eggplant was selected to be used in robotic harvesting systems. When the modeling results were compared with previous studies, it was seen that they showed parallelism according to the study criteria. In all studies, YOLOv5 was found to be the best model. Differences were determined in the sub-models. This difference was due to the structure of the products used, epoch, batch and image processing pixel values. It was determined that the modeling was suitable for robotic harvesting.

5. Conclusion

The deep learning method has been an important tool in robotic harvesting applications of many products in agricultural automation. Robotic harvesting applications appear as an important method that can contribute to increasing agricultural productivity and reducing labor force. Studies on eggplant harvesting using deep learning methods have a significant potential to increase efficiency and optimize harvesting processes in the agricultural sector. For this reason, in this deep learning model study, it was determined which model gave the best results. In the study, it was determined that the YOLOv5m model was the most successful model to be used in robotic eggplant harvesting. All models were trained with 640×640 images. Metric values such as “metrics/precision”, “metrics/recall”, “metrics/mAP_0.5” and “metrics/mAP_0.5:0.95” of the models created with 12 Batch, 110 Epoch were examined. As a result of the comparisons, it was seen that the “YOLOv5 medium” model had higher metric values than the other models. The YOLOv5m model gave the highest score with F1 score of 85.66%, precision of 95.65%, recall of 96.15%, and mAP at 0.5:0.65 of 78.80%. In this study, the potential of deep learning, especially the YOLOv5m model, in automating the robotic eggplant harvesting process was revealed. According to the results, it was contributed to which model would be more efficient in robotic harvesting applications.

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