RESEARCH ARTICLE

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Detection of artichoke on seedling based on YOLOV5 model

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Abstract
Robotic systems have become essential in the industrial field today. Robotic systems used in many areas of industry enable the development of mechanization of agriculture. Researches in recent years have focused on the introduction of automatic systems and robot prototypes in the field of agriculture in order to reduce production costs. The developed smart harvest robots are systems that can work uninterrupted for hours and guarantee minimum cost and high production. The main element of these systems is the determination of the location of the product to be harvested by image processing. In addition to the programs used for image processing, deep learning models have become popular today. Deep learning techniques offer high accuracy in analyzing and processing agricultural data. Due to this feature, the use of deep learning techniques in agriculture is becoming increasingly widespread. During the harvest of the artichoke, its head should generally be cut off with one or two leaves. One main head and usually two side heads occur from one shoot. Harvest maturity degree is the time when the heads reach 2/3 of their size, depending on the variety character. In this study, classification was made by using the deep learning method, considering the head size of the fruit. YOLOv5 (nano-small-medium and large models) was used for the deep learning method. All metric values of the models were examined. It was observed that the most successful model was the model trained with the YOLOv5n algorithm, 640x640 sized images with 20 Batch, 90 Epoch. Model values results were examined 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 validation dataset. It was determined that the metric data of the "YOLOv5 nano" model was higher compared to other models. The measured value was Model 1= Size: 640x640, Batch: 20, Epoch: 90, Algorithm: YOLOv5n. Hence, it was understood that "Model 1" was the best detection model to be used in separating artichokes from branches in robotic artichoke harvesting.
Keywords: Deep learning,YOLOv5, Description,Classification

INTRODUCTION

Deep learning is an important topic in the field of machine learning and is used in many application areas. This technique is used to identify and learn complex patterns from large data sets. Deep learning algorithms consist of neural networks, and these networks are arranged in layers. Each layer takes the outputs of the previous layer as input and learns more complex features and patterns using these outputs. In this way, deep learning algorithms can discover hidden structures in data and perform complex tasks. Deep learning is a subfield of machine learning that focuses on training artificial neural networks with multiple layers to learn and extract high-level representations from complex data (Deng, 2014). Deep learning is used in many different application areas. Examples of usage areas include image processing, deep learning algorithms, object detection and recognition. In addition, deep learning techniques are used in the field of natural language processing and successful results are achieved in tasks such as text classification, language translation and speech recognition. By analyzing large amounts of data, deep learning algorithms can identify patterns and relationships and use this information to make predictions based on new data. Due to these characteristics, deep learning forms the basis of artificial intelligence applications used in medicine, finance, automotive and many other industries. Deep learning algorithms consist of neural networks, and these networks are organized in layers. In deep learning, neural networks consist of multiple layers of interconnected nodes, known as neurons, that process and transform input data. Each layer in the network receives input from the previous layer and transfers its output to the next layer, enabling hierarchical extraction of features and patterns. While layers closer to the input are responsible for learning low-level features, deeper layers learn more abstract and complex representations (Deng, 2014).

One of the most important advantages of deep learning is that it can automatically learn features from raw data, eliminating the need for manual feature engineering. Deep learning models can learn hierarchical representations directly from data, and this enables them to capture complex patterns and relationships that may be difficult to define clearly. This makes deep learning especially effective in processing large and unstructured data sets such as images, text and audio (Akkus et al., 2017). Deep learning has begun to be widely used in many fields, from medicine to agriculture. It has enabled increasing efficiency, productivity and sustainability in agricultural practices. Various studies on this subject have investigated the application of deep learning in agriculture and highlighted its benefits and challenges. One of the promising areas of deep learning is the development of highly autonomous machines for agriculture. These machines can push safety standards and improve the overall efficiency of agricultural operations (Kamilaris et al., 2018). Another application of deep learning in agriculture is in the field of smart agriculture. Deep learning algorithms can be used to analyze large amounts of data collected from sensors, drones, and satellites, and allow farmers to take data-based decisions regarding crop management, irrigation, and pest control (Yang et al., 2022). This can lead to increased crop yields, reduced resource use and increased sustainability. Deep learning can also be used for plant stress monitoring, crop load prediction, and harvesting in agriculture (Gao et al., 2020). Deep learning algorithms can detect and classify plant diseases by analyzing images and data collected from various sources, and enable early intervention and prevention of crop losses (Saleem et al., 2019). This can significantly increase the productivity and efficiency of disease management in agriculture. In addition to crop management, deep learning methods can also be applied to other aspects of agriculture, such as anomaly detection in Internet of Things (IoT) time series data (Cheng et al., 2022). Precision agriculture is another area where deep learning can produce a significant impact. Deep learning can increase the efficiency and sustainability of precision agriculture by optimizing the control of agricultural production systems, managing agricultural economic systems, and processing agricultural information (Alreshidi, 2019). Despite the numerous benefits of deep learning in agriculture, there are also challenges that need to be discussed. These include the need for a large amount of labeled training data, the interpretability of deep learning models, and the integration of deep learning algorithms into existing agricultural systems (Ryo et al., 2022). Another study by Yang et al. (2022) focused on a small number of learnings in smart agriculture. In the study, the developments, applications and challenges of few-shot learning, which was a subfield of deep learning that aimed to train models with limited labeled data, were discussed. The study highlighted the potential of few-shot learning in discussing the problem of data scarcity in agriculture and enabling the development of accurate and efficient models for a variety of tasks. In the study conducted by Cheng et al. (2022), the use of generative adversarial networks (GANs) with attention mechanisms for anomaly detection in smart agriculture was investigated. In the study, a new approach that combined GANs and attention mechanisms to detect anomalies in time series data collected from IoT devices in agricultural systems, was proposed. Besides, Xiao et al. (2022) presented a deep learning-based method for the detection of weeds in vegetables. In the study, a new approach that used deep learning algorithms to accurately identify and classify weeds in vegetable crops, was proposed. As a result of the study, they identified the potential of deep learning in weed control, which was a critical task in agriculture to provide optimum growth and yield of crops.

Overall, deep learning shows great promise in smart agriculture applications. It offers solutions to various challenges such as crop yield prediction, disease detection, anomaly detection, and weed control. However, there are still challenges to overcome, such as the need for large and diverse datasets, interpretability of models, and addressing data scarcity issues. Future research should focus on addressing these challenges and further exploring the potential of deep learning in smart agriculture.

MATERIAL AND METHODS

Material

Artichoke (Cynara cardunculus) is an edible and medicinal plant with a long history of use dating back to ancient civilizations such as the Egyptians, Greeks and Romans (Acquaviva et al., 2023). It belongs to the Asteraceae family and is known for its distinctive flower heads, which are often consumed as a vegetable. One of the main characteristics of artichoke is its rich phenolic profile, which contributes to its antioxidant properties (Acquaviva et al., 2023). Phenolic compounds such as quercetin and other flavonoids have been detected in artichoke extracts (Wang et al., 2003). It has been indicated that these compounds have inhibitory effects on oxidative stress and may protect against liver damage caused by alcohol consumption (Tang et al., 2017). Artichoke extracts have also revealed potential anti-cancer properties by demonstrating pro-apoptotic activity in colon cancer cells (Villarini et al., 2021). Artichoke is valuable for its nutritional content as well as its antioxidant properties. Studies have evaluated the nutritional value of artichoke heads and reported high levels of vitamins, minerals and bioactive compounds (Petropoulos et al., 2018). Artichoke leaves contain several bioactive compounds, including cynarin, which has been studied for its potential cholesterol-lowering effects (Tang et al., 2017). Analytical methods such as colorimetric analyses, thin layer chromatography and high-performance chromatography have been used to analyze phenolic compounds in artichoke leaves (Wang et al., 2003). These methods provide valuable information about the chemical composition of artichokes, enabling the identification and quantification of specific phenolic compounds. In general, artichoke is a versatile plant with potential health benefits due to its antioxidant properties, nutritional content, and bioactive compounds. More research is needed to explore its therapeutic potential and understand the mechanisms underlying its beneficial effects. Artichoke is a type of vegetable whose underground stem is perennial and its above-ground organs are annual, and whose head and leaves are utilized in various ways. The edible part of the artichoke is the large and fleshy floral receptacle of its unopened flowers and the fleshy bottom parts of the artichoke head, which we call bracts. In addition to fresh consumption, it is canned and deep frozen (Anonymous, 2023a). Artichoke harvesting should be done when the heads have reached their normal size but the bracts have not opened. If the harvest is delayed, the bracts open, the floral receptacle gains a fibrous structure and loses its market value. The heads that reach harvest maturity should be harvested with stems 5 to 10 cm long. After harvesting the artichoke heads, the branches and leaves of the plant dry up and the plant enters a resting period, and no processes are performed during this period. Depending on the region, wake-up irrigation is done in July and August. The years with the highest artichoke production are the 3rd and 4th years. Therefore, it is recommended to renew the plantation after the 4th and 5th years. The number of fruits per plant varies between 3-4 (Anonymous, 2023b).

Method

While preparing the dataset of artichoke vegetable, which was targeted for object detection and analysis within the project, harvest photos and videos taken in the fields of the producers in Tekirdağ Naip Village were used. Sample photos are given in Figure 1. Many artichoke images taken during harvest and growth in the vineyard were collected. Among the images obtained, the images that we could not evaluate within the scope of our project were eliminated. We identified 150 images that would be reliable for our object detection study. In addition, there may be more than one artichoke in each image.

Figure 1. Examples of photos taken in the producer's field in Tekirdağ Naip Village

Labeling

The essential element in an object detection model is the labeling of the objects to be used in the training set. Visual labeling was done on Roboflow, a popular website. RoboFlow is a platform used in various research studies and applications. It acts as a source for datasets and helps to pre-process and manage image data. In general, Roboflow provides access to datasets and facilitates the pre-processing and management of image data. It can perform field selection, marking and class labeling on the data images to be processed. This marking and labeling process is easily done through the graphical user interface provided by the website. 100 images were used for the training set. In each image, the parts containing the artichoke image were marked with the bounding box area and assigned to the object class "artichoke". The other images and videos were used in the test set. Label Screen is shown in Figure 2.

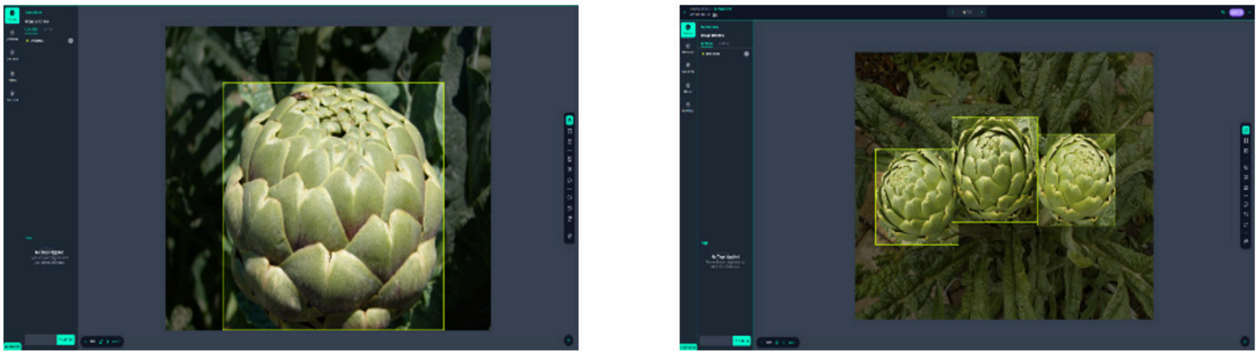


Figure 2. Labeling Screen

Training Model Selection

YOLOv5, one of the deep learning models, was preferred in our study. YOLOv5 is a popular single-stage deep learning algorithm used for object detection. It uses convolutional neural networks (CNN) to detect and classify objects in images. The YOLOv5 algorithm's lightweight structure, improved architecture, and balance between accuracy and speed make it suitable for a variety of applications. YOLOv5 algorithm performs extremely fast processing. It sees the entire image during the training and testing of the data set. Thus, it implicitly encodes contextual information about classes and their views. YOLOv5 learns generalizable representations of objects, and thus shows better performance than other best detection methods when trained and tested on natural images (Nasrullah et al. 2021). YOLOv5 was chosen due to its versatility of usage areas, object detection speed and successful applications in fruit sample segmentation. In the study, YOLOv5n/s/m and l (nano-small-medium and large) models were used in deep learning training. The Yolov5 network structure is shown in Figure 3.

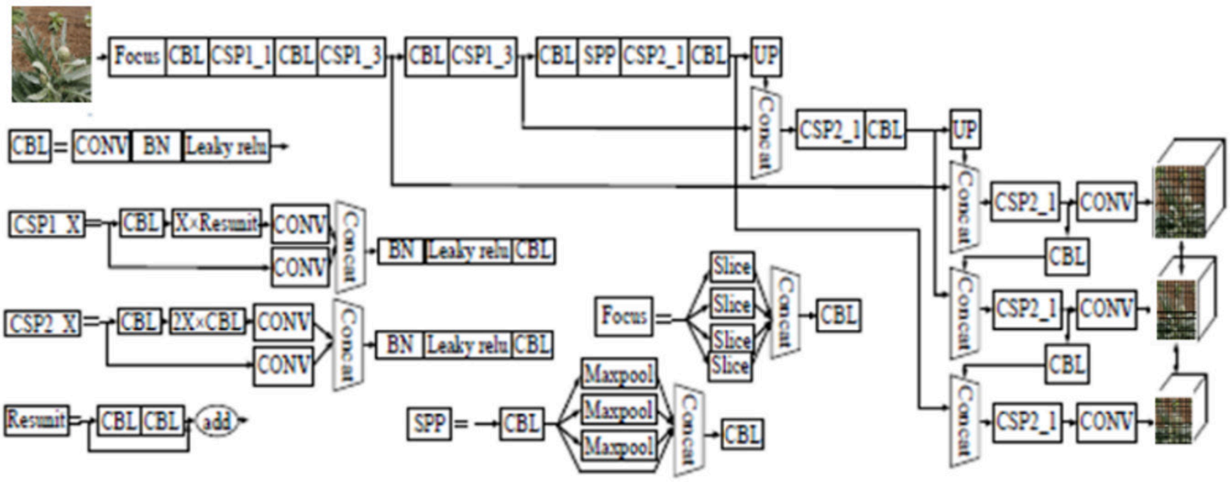


Figure 3. YOLOv5 network structure

Initiation of Training

The training was done with program codes written in the Python ditor with the codes downloaded from GitHub repository, the official site of YOLOv5. The parameters and regulations in the codes written below were preferred for training.

Python train.py –img 640 –batch 20 –epochs 90 –data dataset.yaml –weights yolov5n.pt

python train.py –img 640 –batch 20 –epochs 90 –data dataset.yaml –weights yolov5s.pt

python train.py –img 640 –batch 20 –epochs 90 –data dataset.yaml –weights yolov5m.pt

python train.py –img 640 –batch 20 –epochs 90 –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 640x640, and it was chosen in this way here as well.

-- **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 that 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 these code lines, the training process of the models 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).

Evaluation Indicators

Three types of evaluation indicators are generally used to evaluate the model in the field of target detection: Precision, Recall and mAP (mean Average Precision) which is a combination of the first two. Precision represents the total amount of information obtained, that is, the rate of positive samples among all samples in the detection results. TP (True Positive) indicates that both the detection result and the true value are artichoke; FP (False Positive) indicates the number of samples marked as false but detected as positive samples, i.e., the number of false artichokes detected; FN (False Negative) indicates the number of samples marked as positive but predicted as negative classes, i.e. the number of detected artichokes missed. The larger the mAP value, the better the algorithm detection effect and the higher the pattern recognition performance. Here;

Accuracy is the rate of correct classifications/predictions to the total amount of data. Although the problem with the accuracy metric approaching 1 can be stated as successful, it is not sufficient to comment only on this metric.

Accuracy=(TN+TP)/((TP+FP+TN+FN))

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

Error Rate=(FN+FP)/((TP+FP+TN+FN)) or (1-Accuracy)

Precision measures model accuracy in artichoke detection by determining the rate of TPs to the total number of predictions made by the model. It is the rate of the positive predictions made in the problem to the accurately positive ones, in other words, the correct ones. The precision value can be calculated using the equation given below.

Precision=TP/((FP+TP))

Recall evaluates the model's ability to correctly identify artichokes among all positive targets, including FN detections or those initially missed and undetected. The equation that calculates how many of the observations that should be predicted correctly are predicted correctly is given below.

Recall=TP/((TP+FN))

F1-Score: It is a metric that can be used instead of accuracy and is very important in terms of interpreting and observing the problem. It is the score resulting from the harmonic average of the Precision and Sensitivity metric values.

F1 Score=(2*Precision)/((Precision+Recall))

mAP: Recall and Precision exhibit a trade-off visualized as a curve by adjusting the artichoke's classification threshold. The area under this recall-precision curve represents the average precision for the artichoke in the model. Averaging these values for all defined classes gives the mean average precision (mAP) that can be calculated. The equation used for the average precision is given below.

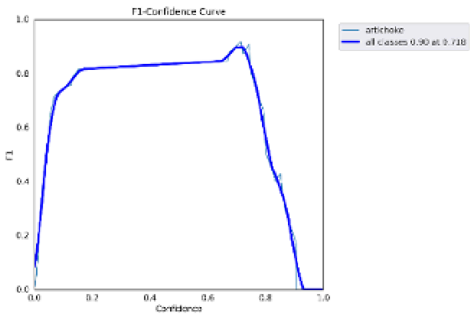
$$\mathrm{mAP} = \frac{1}{\mathrm{C}} + \sum_{\mathrm{k}=1}^{\mathrm{T}} \mathrm{P(k)}\Delta\mathrm{R(k)}$$

RESULTS

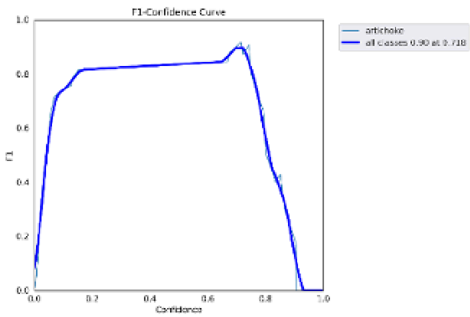
Examination of the results of YoloV5 algorithms according to error matrix metrics

F1 Score

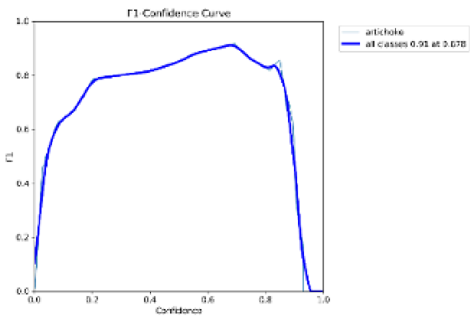
Size: 640x640, Batch: 20, Epoch: 90, Algorithm: YOLOv5n



Size: 640x640, Batch: 20, Epoch: 90, Algorithm: YOLOv5s



Size: 640x640, Batch: 20, Epoch: 90, Algorithm: YOLOv5m



Size: 640x640, Batch: 20, Epoch: 90, Algorithm: YOLOv5l

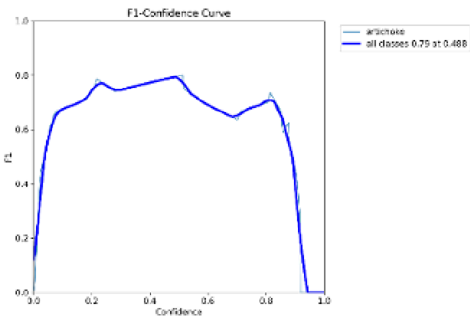
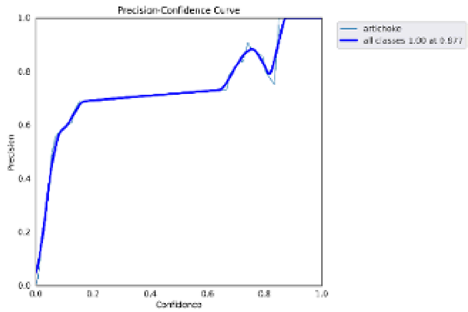


Figure 4. F1 performance score graphs of Yolov5 models

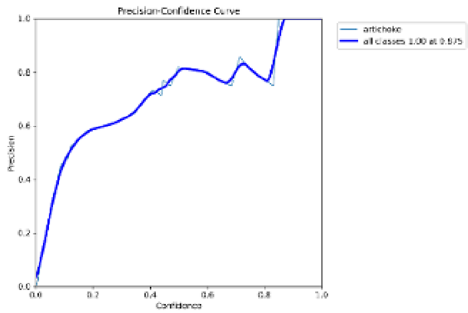
Model 1: F1 score measures the balance between accuracy and false positive rate. This score takes a value between 0 and 1, and the closer it is to 1, the better the performance of the model. The F1 score in the image was determined as 0.85 and indicated that the model had a good performance.

Precision

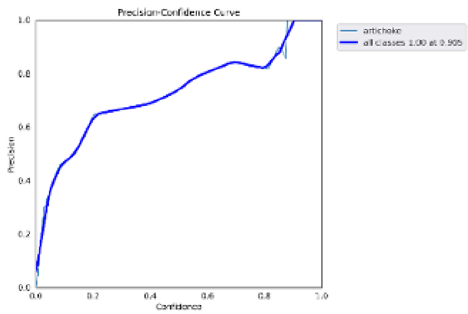
Size: 640x640, Batch: 20, Epoch: 90, Algorithm: YOLOv5n



Size: 640x640, Batch: 20, Epoch: 90, Algorithm: YOLOv5s



Size: 640x640, Batch: 20, Epoch: 90, Algorithm: YOLOv5m



Size: 640x640, Batch: 20, Epoch: 90, Algorithm: YOLOv5l

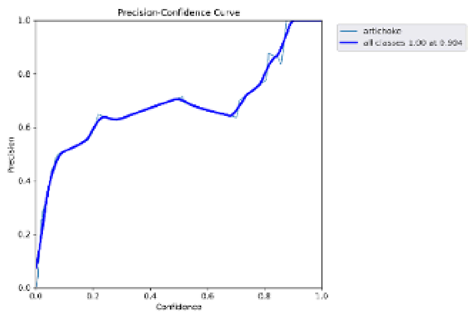


Figure 5. Analysis graphs of precision values obtained in object detection of YOLOv5 models

Model 1: The Precision score indicates that approximately 85% of the model's positive predictions are actually positive. This high precision value indicates that the model's positive predictions are mostly true and the rate of false positives is low.

Recall

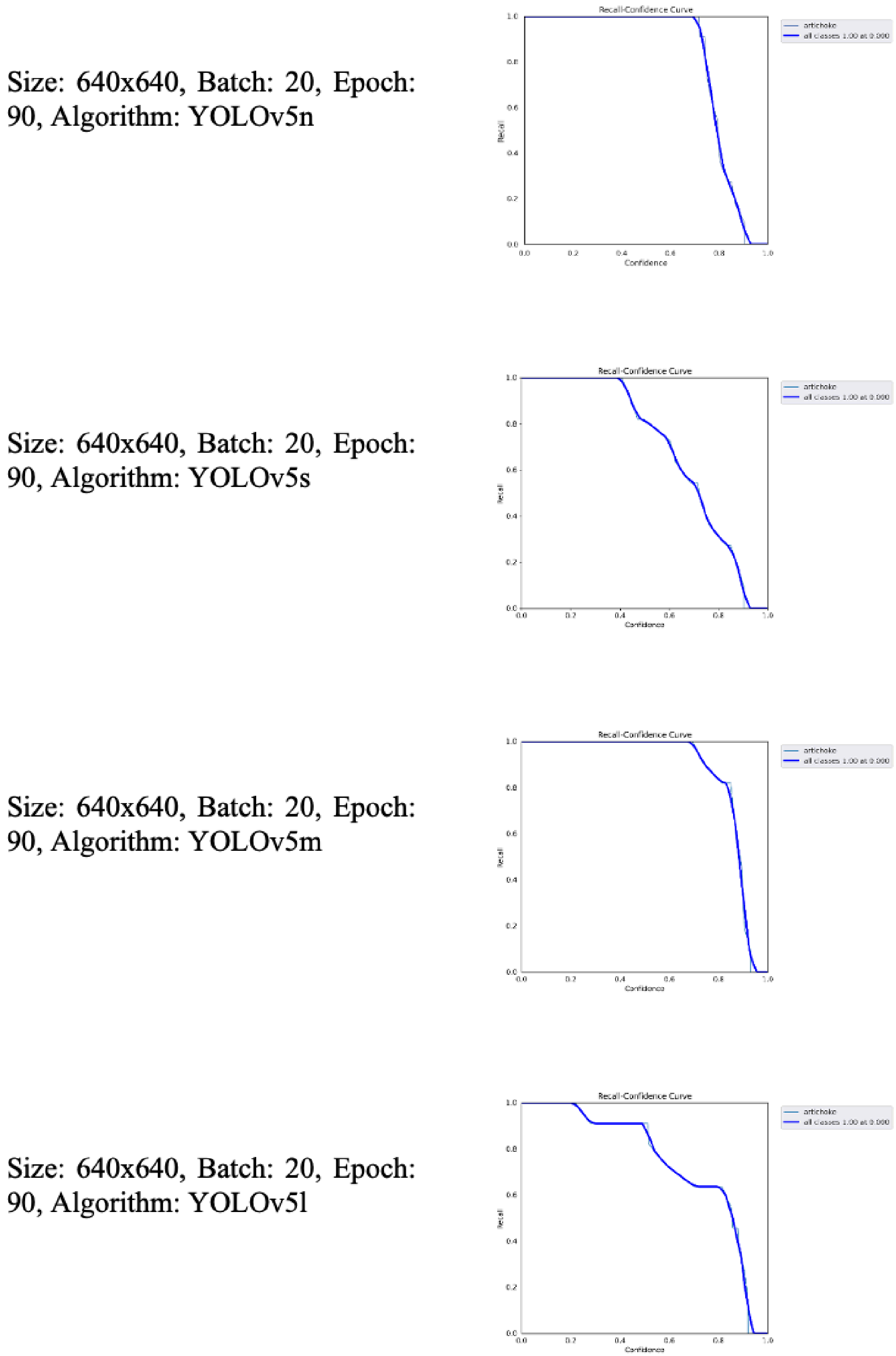
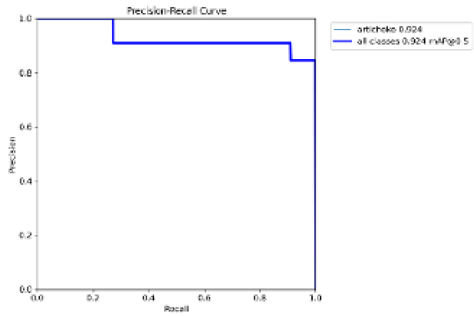


Figure 6. Analysis graphs of recall values obtained in object detection of YOLOv5 models

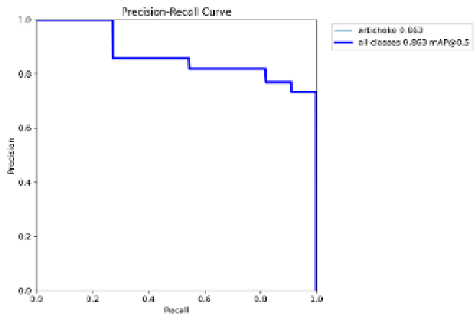
Model 1: A high Recall value shows that the model does not miss the positive class and has a high ability to capture true positives.

Precision Recall

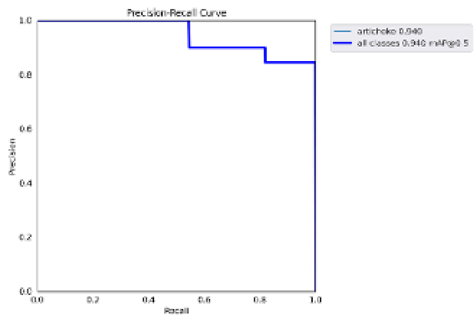
Size: 640x640, Batch: 20, Epoch: 90, Algorithm: YOLOv5n



Size: 640x640, Batch: 20, Epoch: 90, Algorithm: YOLOv5s



Size: 640x640, Batch: 20, Epoch: 90, Algorithm: YOLOv5m



Size: 640x640, Batch: 20, Epoch: 90, Algorithm: YOLOv5l

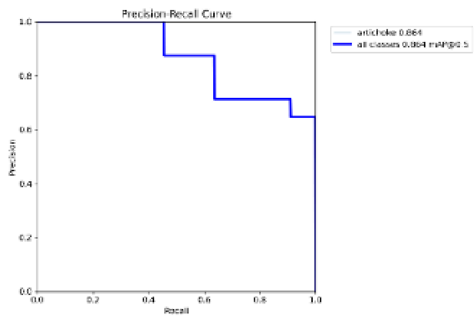


Figure 7. Analysis graphs of precision and recall values obtained in object detection of YOLOv5 models

Model 1: According to the Recall score, the model successfully predicts the majority of true positives. A high Recall score indicates that the precision of the model is high. High Recall usually comes with lower Precision and the number of false positives may increase. Therefore, there should be a balance between Precision and Recall when evaluating the performance of the model.

Loss Function

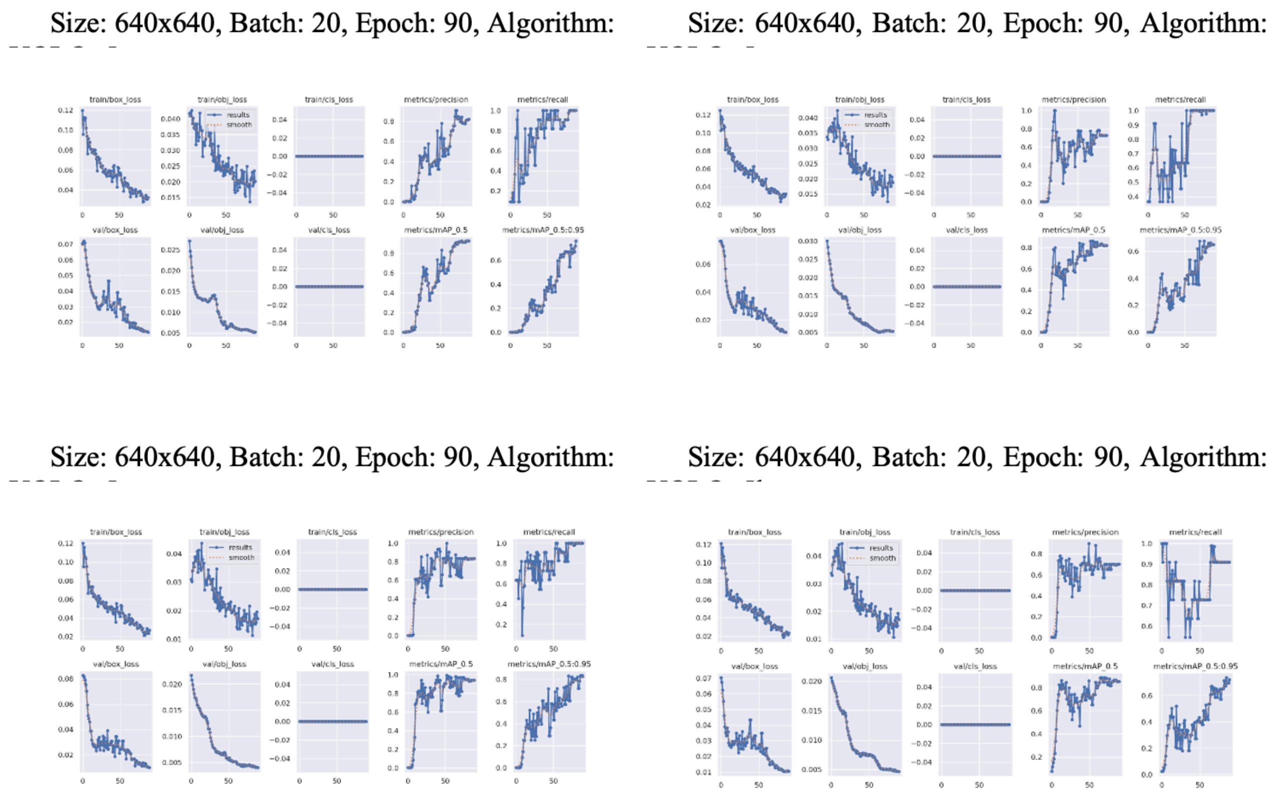


Figure 8. Graphs of error rates and performance values of YOLOv5 models

Model 1: It can be seen that the errors of the model generally decrease over time. This means that the model generally gets better during the training process and its predictions become closer to the true values. However, it seems that the graph fluctuates at certain stages. Therefore, although the overall trend is positive, it is important to identify strategies to further improve the performance of the model and overcome situations that cause these high error rates.

These models differ primarily in their size and complexity, which affect their speed and performance. A comparison based on training results is given below.

Model 1: YOLOv5 NANO

Precision (metrics/precision): 0.81905

Recall (metrics/recall): 1

Average Precision (metrics/mAP_0.5): 0.92388

Tightly Constrained Average Precision (metrics/mAP_0.5:0.95): 0.76145

This model has the highest values in precision and recall metrics, but the tightly constrained average precision is lower.

Model 2: YOLOv5 SMALL

Precision (metrics/precision): 0.7269

Recall (metrics/recall): 1

Average Precision (metrics/mAP_0.5): 0.81932

Tightly Constrained Average Precision (metrics/mAP_0.5:0.95): 0.6499

This model has slightly lower values in precision and recall metrics, but still performs well.

<u>Model 3: YOLOv5 MEDIUM</u>

Precision (metrics/precision): 0.83338

Recall (metrics/recall): 1

Average Precision (metrics/mAP_0.5): 0.94031

Tightly Constrained Average Precision (metrics/mAP_0.5:0.95): 0.82572

This model has the highest precision and recall values at epoch 85. It also has high values in the average precision and tightly constrained average precision metrics.

<u>Model 4: YOLOv5 LARGE</u>

Precision (metrics/precision): 0.7017

Recall (metrics/recall): 0.90909

Average Precision (metrics/mAP_0.5): 0.86324

Tightly Constrained Average Precision (metrics/mAP_0.5:0.95): 0.72314

Although this model has lower average precision at epoch 85, the recall value is high. The tightly constrained average precision metric is also high.

Training Result

Size: 640x640, Batch: 20, Epoch: 90, Algorithm: YOLOv5n

Size: 640x640, Batch: 20, Epoch: 90, Algorithm: YOLOv5s

Size: 640x640, Batch: 20 Epoch: 90, Algorithm: YOLOv5m

Size: 640x640, Batch: 20, Epoch: 90, Algorithm: YOLOv5l

Figure 9. Validation Batch" prediction markings resulting from the training of the models

Comparison of Model Algorithms

The metric data of Model "1" and the difference of other models to these data are shown in Table 1.

Table 1. The metric data of Model "1" and the difference of other models to these data

Model	metrics/precision	Difference (Model 1)	Model	metrics/recall	Difference (Model 1)
Model 1	**0.81905**		**Model 1**	**1**	
Model 2	0.7269	0.09215	Model 2	1	0
Model 3	0.83338	-0.01433	Model 3	1	0
Model 4	0,7017	0.11735	Model 4	0.90909	0.09091
Model	**metrics/mAP_0.5**	**Difference (Model 1)**	**Model**	**metrics/mAP_0.5:0.95**	**Difference (Model 1)**
Model 1	**0.92388**		**Model 1**	**0.76145**	
Model 2	0.81932	0.10456	Model 2	0.66264	0.11155
Model 3	0.94031	-0.01643	Model 3	0.78656	-0.06427
Model 4	0.85324	0.07064	Model 4	0.73866	0.03831

Model 1 has a precision of 0.81905 and a recall value of 1, indicating that it achieves a high precision when capturing all positive samples. Model 2 has a lower precision of 0.7269, indicating a higher false positive rate compared to Model 1. However, it has the same recall value of 1, suggesting that it captures all positive samples. Model 3 has a precision of 0.83338, slightly higher than Model 1, but has a lower recall of 1, indicating that it may miss some positive samples. Model 4 has a precision of 0.7017 and a recall rate of 0.90909, indicating a lower precision and a higher false positive rate compared to Model 1.

In addition to precision and recall, average mean precision (mAP) is another important metric to evaluate the performance of the model. The mAP value of Model 1 is 0.92388, indicating a high average precision between different thresholds. Model 2 has a slightly lower mAP value of 0.81932, indicating a lower average precision compared to Model 1. Model 3 has a higher mAP of 0.94031, indicating a higher average precision. Model 4 has a mAP of 0.85324, indicating a lower average precision compared to Model 1.

Overall, Model 1 performs consistently well in terms of precision, recall, and mAP, and shows its efficiency in capturing positive samples and minimizing false positives. Model 2 shows a decrease in precision compared to Model 1, while Models 3 and 4 have varying performance in terms of precision and recall. However, it is seen that the model with the least loss values in box estimation and object detection losses in the validation data is "Model 1". Training data comparisons of the models are given in Table 2.

Table 2. Comparison of the models according to the training data

Model	train/box_loss	Difference (Model 1)	Model	train/obj_loss	Difference (Model 1)
Model 1	**0.03247**		**Model 1**	**0.020163**	
Model 2	0.032098	0.000372	Model 2	0.018794	0.001369
Model 3	0.026736	0.005734	Model 3	0.017179	0.002984
Model 4	0.023352	0.009118	Model 4	0.017004	0.003159
Model	val/box_loss	Difference (Model 1)	Model	val/obj_loss	Difference (Model 1)
Model 1	**0.013598**		**Model 1**	**0.0051987**	
Model 2	0.011416	0.002182	Model 2	0.0052638	-0.0000651
Model 3	0.0097465	0.0038515	Model 3	0.0040057	0.001193
Model 4	0.010439	0.003159	Model 4	0.0046527	0.000546

The differences in "train/box_loss" and "train/obj_loss" between Model 1 and other models can be attributed to the use of different loss functions. The fact that Model 1 has a higher loss value compared to other models indicates that it may have a less effective loss function for training. On the other hand, the fact that Models 2, 3, and 4 have lower loss values indicates that the loss functions are more effective in minimizing the difference between predicted and ground truth bounding boxes and object classes.

Model 1 also has higher loss values than other models in terms of "val/box_loss" and "val/obj_loss". This reveals that Model 1 performs worse in terms of object detection and classification in the validation set. The fact that the Models

2, 3, and 4 have lower loss values reveals that they perform better in accurately locating and classifying objects in the validation set.

In general, differences in loss values between Model 1 and other models can be attributed to the choice of loss functions. Models 2, 3, and 4, which have lower loss values, probably use more efficient loss functions such as GH-SSD loss [1] or MC-Loss [2]. These loss functions help to improve the training process and improve the model's ability to accurately detect and classify objects.

Finally, the optimization parameters (x/lr0-1-2) of the models were examined. All models have equal values in these parameters. Parameter values are given in Table 3.

Table 3. Optimization parameters of the models

Model	x/lr0-1-2	Difference (Model 1)
Model 1	0.00032	
Model 2	0.00032	0
Model 3	0.00032	0
Model 4	0.00032	0

The object detection accuracies of YOLOv5 models and sample training and validation images made with the prepared data set were examined. When the metric data and accuracy prediction rates indicating the object detection success of the models were examined, it was confirmed that the training result of the "YOLOv5 nano" model was more successful than the others.

DISCUSSION

In their study, Zhang et al. (2022) performed weed-crop classification and lettuce localization in the field using the SE-YOLOv5x deep learning model. As a result of the study, SE-YOLOv5x had the highest performance in weed and lettuce plant identification with 97.6%, 95.6%, 97.1% and 97.3% precision, recall, mean precision (mAP) and F1-score values, respectively. Based on plant morphological characteristics, the SE-YOLOv5x model found the location of the lettuce stem in the field with 97.14% accuracy. Yang et al. (2022) designed a blueberry recognition model based on YOLOv5. To verify the efficiency of the model, the mAP on the blueberry dataset in the study was 83.2%, which was 2.4% higher than the original network. This proved that the proposed method was useful in increasing the blueberry recognition accuracy of the model. Su et al. (2022) performed a tree trunk and obstacle detection method in a semi-structured apple orchard environment based on the improved YOLOv5s to improve real-time detection performance. As a result of the study, they found the average precision values of the model in spring, summer, autumn and winter as 95.61%, 98.37%, 96.53% and 89.61%, respectively. The model size of the developed model was reduced by 13.6 MB, and the accuracy and average accuracy on the test set were increased by 5.60% and 1.30%, respectively. The average detection time was 33 ms and they determined that an orchard carrier platform would meet the real-time detection requirements. In their study, Fu et al. (2022) investigated the control technology for targeted spraying by applying deep learning and online identification methods with cabbages as the research object. To overcome motion blur and low average precision under strong light conditions during the running of the sprayers, they used an innovative YOLOV5 model embedded with a transformer module to obtain accurate online identification for cabbage fields in complex environments. They determined that the target-oriented spraying system designed in the study achieved the expected experimental results and could provide technical support for field target spraying. Wang et al. (2022) developed a cucumber root-knot nematode detection model based on the modified YOLOv5s model to support the breeding of robust cucumber varieties. In the experimental results, they found that the recall (R) and mAP values of the YOLOv5s-CMS model were improved by 3% and 3.1%, respectively, compared to the original YOLOv5s model. They emphasized that with these values, the model could achieve a better performance in detecting cucumber root-nematode. Wu et al. (2022) conducted a study on the problem of automatic classification of horn mushrooms. To solve the problem, they deeply integrated YOLOv5's single-stage object detection with PSPNet's semantic segmentation and constructed a Y-PNet model and an image segmentation network for real-time object detection. As a result of the experiments, they emphasized that the system can successfully perform real-time grading, which can provide instructive and practical references in the industry. Rong et al. (2022) designed a special end effector for robotic harvesting, which mainly consisted of a flexible gripper and a cutting device to grasp the fruits and cut the pedicles. With the YOLOv5s-CBAM model they developed, they found watermelon fruits with 89.8% accuracy in the test dataset. The overall harvest success rate was 85.0% with positioning error. López-Correa et al. (2022) evaluated a new method to automatically detect and classify the most problematic weed species in tomato crops in one step. The procedure is based on object detection neural networks called RetinaNet. They also evaluated two existing mainstream object detection models, YOLOv7 and Faster-RCNN, as a one- and two-stage NN, respectively, in comparison with RetinaNet. As a result of the experiments, the prediction model was validated with images that were not used during training under the average precision (mAP) metric. RetinaNet showed an AP value ranging from 0.900 to 0.977, depending on the weed type. Faster-RCNN and YOLOv7 also achieved satisfactory results in terms of mAP, especially through data augmentation. Xie et al. (2022) developed an improved litchi detection model called YOLOv5-litchi for litchi detection in complex natural environments. As a result of the study, they found that the mAP and recall values of the YOLOv5-litchi model were improved by 12.9% and 15%, respectively, compared to those of the unimproved YOLOv5 network. They found that the inference speed of the YOLOv5-litchi model to detect each image was 25 ms, and they emphasized that this speed was much better than Faster-RCNN and YOLOv4. Fu et al. (2022) developed a dynamic detection method based on an improved YOLO-v5 network for an accurate broad bean phenotype definition. In the experimental phase, they analyzed the effect of different data sets on the model and the performance of different models on the same data set under the same test conditions. When the test results were compared with the network models trained on the RGB dataset, they found that the recall and precision of the models trained on the RGB-D dataset increased by approximately 32% and 25%, respectively. As a result of comparison with YOLO-v5s, they found that the precision of the improved YOLO-v5 increased by approximately 6%, with a precision of 88.14% for the determination of the amount of broad bean with 200 plants in the soybean population.

This study was conducted to determine the best deep learning detection model that can be used for robotic harvesting of artichokes. The YOLOv5 model was also used successfully in the current studies we mentioned. It was observed that the results in the studies were parallel to the results found in the study. The study indicated the potential of using crop identification for robotic systems in artichoke harvesting. All metrics of YOLOv5 were examined to increase the performance of robotic systems to be designed for use in artichoke harvesting. It was observed that such performance evaluations will be of great importance for the development and optimization of robotic harvesting systems.

CONCLUSIONS

In this study, YOLOv5 deep learning model was used to detect artichoke on seedlings. All sub-algorithms of the model were applied in the study. The detection success of the models on artichoke seedlings was examined as metric and validation prediction values. It was determined which sub-model of YOLOv5 gave the best results according to the success rates in object detection, metric and verification prediction values. According to loss values and learning speed rates, the best sub-algorithm model was confirmed as YOLOv5nano. The training of each sub-model was performed as Size: 640x640, Batch: 20, Epoch: 90. As a result of the testing phase, it was seen that the value python train.py --img 640 --batch 20 --epochs 90 --data dataset.yaml --weights yolov5n.pt gave the best results. It was understood that the higher Precision value of the YOLOv5n model compared to other models increased the success of the model. The information obtained from this research will greatly facilitate the detection and robotic harvesting of artichokes on seedlings.

COMPLIANCE WITH ETHICAL STANDARDS

Peer-review

Externally peer-reviewed.

Conflict of interest

The authors declare that they have no competing, actual, potential or perceived conflict of interest.

Author contribution

The contribution of the authors to the present study is equal. All the authors read and approved the final manuscript. All the authors verify that the text, figures, and tables are original and that they have not been published before.

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Ethics committee approval is not required.

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

Consent to participate

Not applicable.

Consent for publication

All authors consented to the publication of this manuscript.

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