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Research Article

Deep Learning for Apple Branch Detection: an Analysis of the Performance of YOLOV8 Models

Erhan KAHYA*

Department of Electronics and Automation, Tekirdag Namik Kemal University, Turkey

***Corresponding Author:** Erhan KAHYA, Department of Electronics and Automation, Tekirdag Namik Kemal University, Turkey.

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Abstract

Thanks to developments in the field of deep learning in recent years, important results have been achieved in various research projects. The YOLOv8 model, which is primarily used for object detection, exhibits varying degrees of superiority in certain tasks with its different sub-models. In specific evaluations such as classification, identification and disease detection, the subcomponents of each model show different performance in their own areas. The characteristics of all sub-models of YOLOv8 were analysed and it was determined which model has speed, resource utilisation, high accuracy and balanced performance. The study focuses on the optimization of apple detection by integrating deep learning approaches. Four different models of Yolov8 (YOLOv8S, YOLOv8M, YOLOv8L and YOLOv8XL) are analysed to accurately detect apples on branches. In the experimental analysis, a comprehensive evaluation was conducted using performance metrics such as accuracy, recognition value and mean accuracy (mAP) of each model. The results show that the YOLOv8S model stands out for its fast processing and low cost advantage, while the YOLOv8XL model offers the highest accuracy. In addition, the YOLOv8M model was characterised by high recognition rates.

Keywords: Deep Learning; YOLOv8; Identification; Apple

Introduction

The modern agricultural industry is increasingly relying on automation and precision farming techniques to increase yields and reduce labour costs. In particular, accurate detection of fruit on the branch is critical for automated harvesting systems, yield estimation, and overall orchard management. Orchards have complex structures characterised by variable lighting conditions, dense foliage, and various branch configurations. These complex structures cause significant challenges in computational sensing tasks. Deep learning has started to be used in object detection tasks, especially with the help of recent advances in convolutional neural networks (CNNs). In particular, thanks to the integration of convolutional neural networks (CNNs) and real-time detection frameworks such as YOLO (You Only Look Once), the accuracy and efficiency of fruit detection systems have increased significantly and have become indispensable tools for modern agricultural applications [1].

Harvest criteria of apples play a critical role in terms of improving fruit quality and extending the storage period. Harvest time is determined depending on the maturity level of the apple, and various physical and chemical parameters are taken into account in this process. Apple harvest time can be analysed through criteria such as starch content, fruit firmness, and sweetness [2,3]. The starch index is a widely used criterion to indicate the ripeness of apples. In his study, [2] reveals how starch levels play a critical role in pre-harvest quality apple production. Since the starch content of apples decreases over time, it is emphasized that fruits with a high starch index should be harvested. Fruit firmness is another important harvest criterion. During the apple harvesting process, fruit flesh firmness is considered a critical indicator in determining the maturity level [3]. In their research examining the effects of small doses of AVG applications on apple firmness, they showed that these applications increased the durability of the fruit flesh. The increase in fruit firmness and the observation of dynamic changes during the ripening process of apples help to determine the correct harvest time. The external appearance and colour of the apple are also important factors affecting the harvest decision. The colour and surface quality of the apple are among the important criteria in determining the harvest time, and these factors constitute an important factor in terms of both visual quality and consumer preferences [4]. In this context, it can be said that apples start to ripen between June and September, so observations and measurements made during this period will be decisive for harvesting.

The detection of apples on branches using deep learning is seen as a significant advance in precision agriculture. This progress has enabled the use of advanced algorithms to increase agricultural productivity through fruit identification. With the increasing demand for efficient agricultural practices, the integration of deep learning technologies, especially in image analysis and object detection, has optimised fruit harvesting. Using techniques such as Convolutional Neural Networks (CNNs) and innovative pre-processing methods, researchers have developed robust models that can precisely locate apples in various environmental conditions, thereby improving both yield and resource management [5,6].

The main studies on apple detection utilise advanced image preprocessing techniques that improve the quality of the input data and reduce the challenges of complex backgrounds. Methods such as data normalisation, image enhancement, and contextual background removal have been effective in improving model performance, enabling algorithms to learn from a variety of perspectives and conditions [7,8]. Furthermore, the development of frameworks such as the Advanced Deep Learning Framework (ADLF) has shown statistically significant improvements in detection accuracy and efficiency compared to traditional models, demonstrating the potential for these approaches to revolutionise fruit detection in agricultural settings [9].

Despite these advances, deep learning applications in apple detection also face some challenges. Issues such as the need for large volumes of high-quality data, susceptibility to overfitting, and the need for continuous updating are among the major concerns. The integration of reliance on real-time data and the adaptation of models to specific environmental conditions maximises their effectiveness in practical applications [10,11]. With the advancement of technology, the implications for agricultural productivity and environmental sustainability are profound and could foster a new era of smart agriculture that leverages data-driven insights for improved decision making and efficiency in fruit production [12,13].

The advent of datasets such as NeRDS 360 and annotated collections has enabled the development of algorithms that effectively identify and classify apples in complex natural environments [1,9]. Key methodological approaches include Faster Region-based Convolutional Neural Networks R-CNN, which uses Region Proposal Networks (R-PNN) to improve detection accuracy, and semantic segmentation techniques that deal with overlapping fruits and variable light conditions [14,15]. These innovations have led to successful applications in real-time yield forecasting and improved operational efficiency by helping to provide valuable information to farmers as part of crop management [16]. However, despite technological advancement, there are still challenges in apple detection, such as data scarcity, variations in fruit characteristics, and environmental factors that can negatively affect detection accuracy [17]. In addition, computational efficiency is also an obstacle, as training deep learning models often requires significant computational resources, especially for real-time applications. Addressing these issues is crucial for the wider application of these technologies in agriculture and for providing reliable and scalable solutions for crop detection [18].

This study aims to improve the efficiency of deep learning applications in the detection of apples on branches. In particular, by comparing the performance of different YOLOv8 models (YOLOv8S, YOLOv8M, YOLOv8L, and YOLOv8XL), the most effective method in terms of accuracy and speed in apple detection will be determined. The research aims to develop a robust and scalable solution to optimise apple harvesting processes and increase agricultural productivity. This approach will highlight the potential benefits of deep learning technologies in agricultural applications and identify directions for future research.

Materials and Methods

Data Acquisition

YOLOv8 (You Only Look Once v8)

In this study, the YOLOv8 version of the YOLO model family, which was developed using the Convolutional Neural Network (CNN) method, is preferred. YOLOv8 is a widely used and developed algorithm for object detection in various domains.

It is a deep learning based computer vision model developed by Ultralytics and used in tasks such as real-time object detection, segmentation, classification, and tracking. It is the most up-to-date and advanced version of the YOLO series. YOLOv8 is a model that detects objects by analysing images in one go (Figure 1).

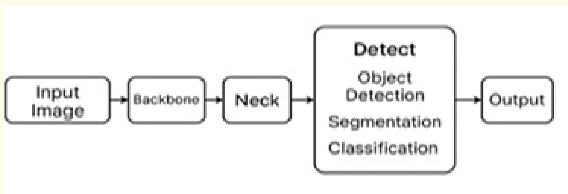


Figure 1: Yolov8 block diagramı.

The basic structure of this model consists of several crucial stages

- **Input layer:** First, the model receives the input image and preprocesses it.
- **Feature extraction:** The first layers in a Convolutional Neural Network (CNN) focus on extracting low-level features in the image, namely edges and corners. This layer is one of the most important components of deep learning.
- **Feature fusion:** The features obtained at various scales are combined. In this way, it is possible to recognise both small and large objects.
- **Object classification and localization:** The final layers of the model estimate the bounding boxes around the objects based on the extracted features and determine which class each object belongs to.

The most remarkable aspect of YOLOv8 is that it provides fast results by performing all these operations in a single step. This feature offers great advantages for real-time systems such as security cameras, autonomous driving systems, and smart city applications. By scanning the image in a single pass, the model can simultaneously calculate the presence of potential objects in each region.

The way the model works starts with scaling the input image to specific dimensions. In the next step, feature extraction is performed by CNN layers. In each layer, activation functions are used to optimise the distribution of data within the network (Figure 2).

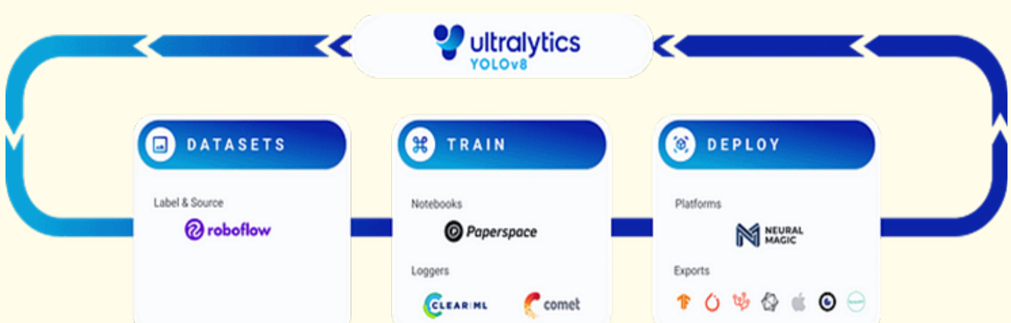


Figure 2: YOLOv8 application diyagram [19].

Features of YOLOv8

- **Improved Performance:** Faster and more accurate than previous versions, better overall accuracy (mAP), and lower inference time.
- **Plug-and-Play Usage:** Very easy installation and use thanks to Ultralytics' ultralytics Python package.CLI (command line) and Python API support.
- **Multi-Task Support:** Object Detection.Instance Segmentation. Classification.Tracking
- **Export Feature:** It can be exported to different formats such as ONNX, TensorRT, CoreML, OpenVINO, and TFLite.
- **Anchor-Free Structure:** YOLOv8 uses an anchor-free architecture. In this way, it has a simpler and more flexible structure.

Performance evaluation criteria

To start training the model for apple detection, first open the Python Runner editor. After running the program train.py, which provides the YOLOv8 training in the main directory of the editor, the parameters and edits listed below have been made.

- python train.py --img 640 --batch 16 --epochs 100 --data dataset.yaml --weights yolov8s.pt
- python train.py --img 640 --batch 16 --epochs 100 --data dataset.yaml --weights mpt
- python train.py --img 640 --batch 16 --epochs 100 --data dataset.yaml --weights yolov8l.pt
- python train.py --img 640 --batch 16 --epochs 100 --data dataset.yaml --weights yolov8xl.pt

Five index parameters were used to evaluate the performance of the network model: accuracy P (Precision, %), recall R (%), mean average precision (mAP), and F1.

The equations used in the calculation are shown below.

$$P = \frac{TP}{TP + FP}$$

$$R = \frac{TP}{TP + FN}$$

$$F1 = \frac{P \text{ x } R \text{ x2}}{P + R}$$

In this equation

- TP correctly predicts positive samples as positive,
- FP, negative samples falsely predicted as positive,
- FN, positive samples falsely estimated as negative,
- TN refers to the correct prediction of negative samples as negative.

Average average precision (mAP): The average mean precision is a summarized metric of precision at different recall values. It is calculated by averaging the average precision (AP) values for each class:

$$AP = \int_0^1 P(R)$$

$$\mathrm{m}AP = \frac{1}{N}\sum_{i=1}^{n} APi$$

$$\mathrm{m}AP@50\% = \frac{1}{N}\sum_{t=1}^{n} AP@0.5$$

Here:
AP_i: Average precision for class i.
N: Number of classes.

Also, k represents the current class, and M represents the total number of classes.

Accuracy (precision) is expressed as the proportion of truly positive instances out of all instances predicted as positive.

Recall refers to the proportion of all true positive samples that are correctly predicted to be positive.

Labelling

Labelling in deep learning is about assigning the 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, the objects that are to be recognised must first be marked in the data set. For this reason, each of the 500 apple images taken from the website universe.roboflow.com was provided with bounding box areas.

Research Results and Findings

F1 Score, Precision, Recall, and mAP@50 value graphs of the results of YOLOv8 algorithms according to the error matrix metrics are analysed. F1 Score, precision, recall, and mAP@50 value graphs are given in Figure 3 below. Figure 4 shows the test set output images, and Figure 5 shows the validation set output images (Table 1, Figure 3-5).

Model	F1 Score	Precision	Recall	mAP@50
YOLOv8M	0.8273	0.8099	0.8455	0.8380
YOLOv8L	0.7773	0.7829	0.7719	0.7859
YOLOv8S	0.8683	0.8763	0.8605	0.8816
YOLOv8XL	0.7975	0.7932	0.8019	0.8006

Table 1: Test result values.

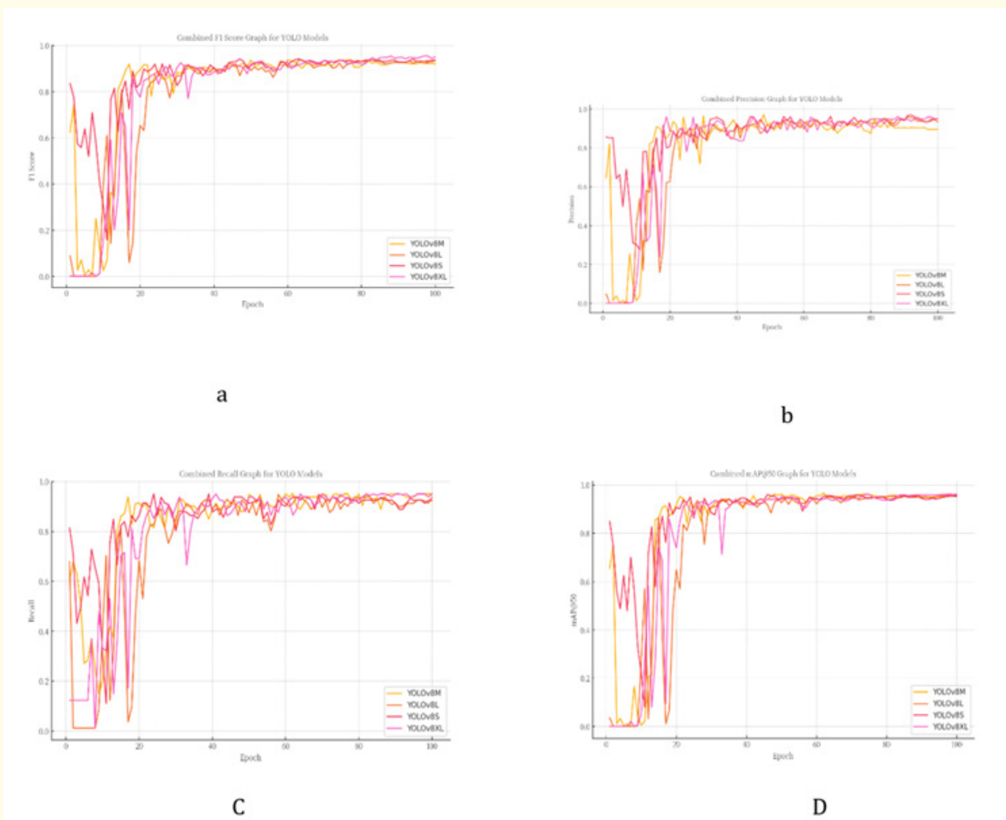


Figure 3: a -F1 score,b-Precision,c-Recall,d-mAP@50.

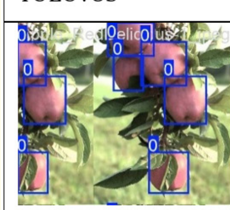
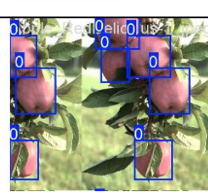
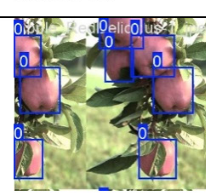
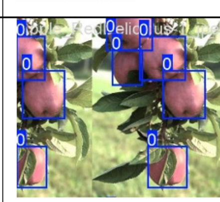
YOLOv8S	YOLOv8M	YOLOv8L	YOLOv8XL
			

Figure 4: Test set images.

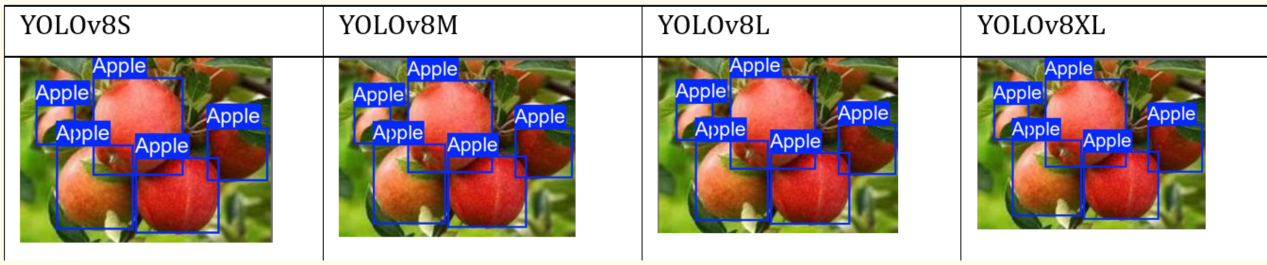


Figure 5: Valid set images.

According to these figures and values

- **YOLOv8S:** The small-scale model offers a quick start and low calculation costs with a low number of parameters.
- **YOLOv8M:** The medium-scale model tends to achieve a higher hit rate, which is important to minimise the number of undetected apples.
- **YOLOv8L:** The large model shows a performance that is balanced with the increase in capacity.
- **YOLOv8XL:** It is the largest model and shows the best results in overall accuracy, achieving the highest precision and recognition scores in the last epochs.

The training data for each model was analysed with early (epochs 1-10) and late (epochs 90-100) observations, and the schedule remained constant throughout the learning rate (lr/pg0, lr/pg1, lr/pg2).

Detailed model-based analysis

YOLOv8S model

Period	Precision	Recall	mAP50	mAP50-95
First (1–10)	~0.857	~0.815	-	-
Last (90–100)	~0.942	~0.914	~0.945	~0.892

Table 2: Analysis of precision, recall, and mAP for YOLOv8S.

The early drop is due to the increase in learning rate and the lack of stabilisation of weight updates. The final performance shows that the model is stable and very accurate.

Loss Type	Initial Value	Final Value
Box Loss	~0.612	~0.228
Cls Loss	2.042	~0.197
DFL Loss	1.121	~0.859

Table 3: Analysis of the loss functions.

The validation loss indicators show that the model degrades and converges during the training process.

- **Analysis of the optimization parameters:** The learning rate starts at 0.00026 at the beginning, increases to 0.00182 around epoch 10, and decreases to about 3.98e-05 at epoch 100.

YOLOv8M model

Period	Precision	Recall	mAP50	mAP50-95
First (1-10)	~0.647	~0.605	-	-
Last (90-100)	~0.905-0.895	~0.948-0.950	-	-

Table 4: Analysis of precision, recall and mAP for YOLOv8M.

The sudden drop in the first epochindicates a temporary stabilisation problem during the parameter update of the model.

Loss Type	Initial Value	Final Value
Box Loss	~0.376	~0.293
Cls Loss	-	~0.253
DFL Loss	-	~0.912

Table 5: Analysis of the loss functions.

Although 'inf' or 'nan' values are observed in the first epochs, this situation then stabilises.

- **Analysis of the optimization parameters:** The learning rate strategy is similar to YOLOv8S. It provides height after the fluctuations of the first period.

YOLOv8L model

Period	Precision	Recall	mAP50	mAP50-95
First (1-10)	~0.048	-	-	-
Last (90-100)	~0.947	~0.914	~0.951	~0.871

Table 6: Analysis of precision, recall and mAP for YOLOv8m.

Initially, the fitting time was slow, but high accuracy and stability were achieved.

Loss Type	Initial Value	Final Value
Box Loss	~0.659	~0.277
Cls Loss	2.885	~0.239
DFL Loss	1.176	~0.893

Table 7: Analysis of the loss functions.

The validation losses decreased significantly as the training process progressed.

- **Analysis of the optimization parameters:** The learning rate plan follows a similar trajectory: stabilisation with a gradual transition to decline.

YOLOv8XL Modeli

Period	Precision	Recall	mAP50	mAP50-95
First (1-10)	~0.00054	~0.123	-	-
Last (90-100)	~0.9506	~0.9505	~0.9618	~0.8795

Table 8: Analysis of precision, recall and mAP for YOLOv8XL.

Thanks to its large capacity, the model achieved results comparable to those of its competitors in terms of final accuracy.

Loss Type	Initial Value	Final Value
Box Loss	~0.691	~0.283
Cls Loss	3.436	~0.263
DFL Loss	1.218	~0.902

Table 9: Analysis of the loss functions.

As the training process progressed, a significant decrease in validation losses was observed.

- **Analysis of the optimization parameters:** The dynamics of the learning rate are the same for all models: the lr values increase as the epoch progresses and then decrease.

Comparative evaluation between the models

Model	First Period Precision	Final Period Precision	Final Period Recall
YOLOv8S	~0.857	~0.942	~0.914
YOLOv8M	~0.647	~0.905	~0.950
YOLOv8L	~0.048	~0.947	~0.914
YOLOv8XL	~0.00054	~0.9506	~0.9505

Table 10: Comparison of precision, recall, and mAP.

YOLOv8XL and YOLOv8S achieve the highest precision value in the last epochs, while YOLOv8M has a high recall value.

Evaluation of the loss functions

A significant decrease in training and validation loss values was observed for all models, indicating a stable training process. The 'inf' or 'nan' values in the early epochs have improved.

Comparison of the learning rate (lr) and the optimization parameters

A common learning rate strategy was followed in all models. Therefore, the differences in performance are due to the architecture structure and parameter capacity.

Discussion

In this study, the performance of different YOLOv8 models for the detection of apples is analysed and the results are compared with similar previous studies. The results of the study show that the YOLOv8S model is characterised by its high speed and low cost, while the YOLOv8XL model provides the best results in final accuracy. In previous research, the superiority of the models was not emphasised by comparing the models with each other. The best result obtained in deep learning is given as the research result. The sub-models of each model show superiority depending on the desired situations. For specific evaluations such as classification, identification and harvest detection, the submodels of each model may show different levels of superiority to each other. In this study, the characteristics of all submodels of the YOLOv8 model were examined to determine which model exhibits speed, resource utilisation, high accuracy, and balanced performance. It has also been shown that deep learning-based object detection algorithms can achieve effective results in precision agriculture applications.

Research into fruit recognition shows the effectiveness of deep learning methods and in particular the YOLO algorithm (You Only Look Once). In one study, the accuracy of fruit detection with YOLOv7 was 51.2%. This rate is considered a very high success compared to existing object recognition algorithms and supports the rationale for favouring the YOLO algorithm in the development of commercial fruit picking robots [20]. By using the YOLO algorithm on datasets created with image processing technologies, highly accurate results were obtained. These results make an important contribution to the development of automation in fruit detection [21]. The AG-YOLO model developed in citrus fruit detection has significantly improved localization success in complex backgrounds, overlaps and natural environmental conditions thanks to advanced techniques such as global context fusion [22]. Similarly, YOLO-based approaches for classifying the ripeness of avocados have shown effective results in analysing and classifying fine details on the fruit surface [23]. In such applications, the ability of the YOLO algorithm to simultaneously perform classification and region prediction provides practical solutions for real-time monitoring and evaluation of agricultural products [24]. In the field of apple detection, pruned YOLO V4-based systems support automated quality control processes by helping to accurately detect and localise defective areas despite poor lighting conditions and background noise [25,26]. The ripeness of nutmegs is determined using the YOLO-R-FEW architecture; CIE-YOLOv5-based methods for blueberries improve fruit detection performance; modelling developed for various fruit types such as mango sizing, pomegranate and olive fruit detection provides important examples for agricultural automation and yield increase [27-29]. Lightweight versions of YOLO designed for real-time use on low-power computers are critical for assessing agricultural productivity in the field and integration into mobile applications [30]. Deep learning (DL) provides a framework that not only improves detection capabilities but also provides the possibility to classify different fruit types with high accuracy. A study proposed 14 different DL models for fruit classification and used pre-trained models from datasets such as ImageNet to improve the performance of these models [31]. Furthermore, the ability of DL algorithms to adapt to various data sets and scenarios demonstrates the potential of these models to solve real-world agricultural problems, as these algorithms can learn from different data inputs [32,33] used the YOLOv8 model for deep learning in kiwi detection and YOLOv8XL was found to be the best model.

The basic architecture used in fruit detection systems consists of convolutional neural networks (CNN) specialised in extracting local features from fruits. The latest generation of object detection models is generally divided into two categories. These are two-stage detectors and one-stage detectors. Two-stage detectors use a RPN to create potential bounding boxes prior to the classification and regression process. Single-stage detectors such as YOLO (You Only Look Once) and SSD (Single Shot Multiple Bin Detector) prioritise detection in terms of speed and efficiency. They operate as regression problems that simultaneously estimate class probabilities and bounding box coordinates [34-36] identified YOLOv8L as the best model in their studies on the detection of persimmon on the branch. [37] integrated Yolov8 technology into the field of plant science. Their goal was to improve the detection of small objects through simple and effective improvements. With the approach they called ‘Yolov8-UAV’, they were able to distinguish small objects in UAV images. [38] found that YOLOv8 is the best model for detecting pepper on the branch.

Deep learning models, especially those based on convolutional neural networks (CNNs), have significant potential in automating tasks related to fruit detection. These models can accurately identify and localise fruits in images, thus facilitating processes such as counting, sorting, and quality assessment [39]. Using a large number of data sets and complex algorithms, these systems can learn to recognise fruits in various conditions and improve their adaptability [40].

Furthermore, this study emphasises the importance of image preprocessing techniques in improving the performance of the models. [8] reported that methods such as image normalisation and contextual background removal help to overcome the difficulties in apple detection. This study supports the necessity of image preprocessing techniques by presenting similar findings. [41] found that YOLOv5m gave the best results in the detection of eggplant on seedlings.

The study aims to improve the performance of apple detection with deep learning algorithms and presents a comparative analysis of four different YOLOv8 models (YOLOv8S, YOLOv8M, YOLOv8L and YOLOv8XL). The results show that the YOLOv8XL model achieves the highest accuracy values, while the YOLOv8S model provides advantages in terms of speed and cost. In addition, the YOLOv8M model has a remarkable performance with high recall rates.

Conclusion

The performance of different YOLOv8 models (YOLOv8S, YOLOv8M, YOLOv8L, and YOLOv8XL) was investigated when recognising apple fruits on branches using deep learning methods. The results show that deep learning-based algorithms play an important role in agricultural productivity. As a result of the study, the YOLOv8S model was found to be characterized by its fast processing capability and low cost advantages. The YOLOv8XL model achieved the highest accuracy value. The YOLOv8 M model was identified as having high recall rates. Metrics such as precision, recall, and mean average precision (mAP) were used to evaluate model performance. The YOLOv8S model achieved high scores of 87.63% precision, 86.05% recall, and 88.16% mAP. As a result of the comparison of the models, it was observed that YOLOv8XL provided the best results, while YOLOv8S demonstrated adequate performance in terms of speed and computational costs. It was concluded that using YOLOv8M would be suitable for applications requiring high recall.

The results suggest that image preprocessing methods have the potential to improve model performance. In particular, the variety and quality of the data significantly influence the success rates of the model.

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