PomeStage: A Deep Learning Approach to Monitoring Pomegranate Growth Phases with YOLO Models

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Abstract. Agriculture has made extensive use of deep learning and machine learning, both of which have grown extremely quickly in recent years. We utilize a dataset of images depicting the growth stages of pomegranates to achieve this. Photographs of the different stages of pomegranate growth were taken in an orchard at the Henan Institute of Science and Technology in China between May and September. The five periods in the dataset are bud, flower, early-fruit, mid-growth, and ripe. The dataset consists of 5,857 images of pomegranates at different stages of growth. In this research, we dive into the elaborate task of pomegranate growth image detection using the YOLO model. The study involves an in-depth analysis of YOLOv8 and YOLOv5 and how well they differentiate between various kinds of Growth of pomegranate. This paper aims to find the best model for our detection. The mAP50 are 90%(yolov8) and 76.8% (yolov5). This may help researchers develop computer applications using machine learning and computer vision algorithms.

Keywords: Feature extraction; Image Detection; Image classification; Pomegranate growth period detection.

1 Introduction

The ancient fruit of pomegranate is well known for its numerous advantages as a healthy food [1] due to the high number of antioxidants that support the healthy working of the heart and kidneys [2] [3] while preserving a balanced microbiome too. This fruit is also becoming of economic relevance, especially in dry climatic [4] regions where the plant is well suited. Knowing when the fruit is at its optimum stage of growth becomes important so that quality and quantity of the fruit's yields are maximized enabling farmers to plan on the time of harvesting. This will help in most cases to save on losses from spoilage in the absence of carrying out sophisticated operations.

Normally, the growth stages of the pomegranate plant were examined by the [5] naked eye which was a labor-intensive process and had room for inaccuracies. As the new century has dawned, there are changes brought by the improved technology that is affecting the latter. Image processing based on [6] Convolutional Neural Networks

(CNNs) [7] and other such models as YOLO [8] (You Only Look Once) are improving the utilization of images in agriculture facilitating the assessment of the health of the crops and the stages of their growth automatically.

The current study employs the YOLOv8 [9] and the YOLOv5 models in the process of detecting the stages of pomegranate growth in real-time from the time the pomegranate blooms to the time its fruits are fully grown. The dataset contains a total of 5,857 food-grade photographs taken in various Chinese Orchards and weather conditions which were ready for training after [10] Roboflow processing.

To evaluate the models' performance, specific performance metrics such as [11] Precision, Recall, and Mean Average Precision (mAP) [12] are applied and the results are given in the form of confusion matrices to indicate where the model needs improvement. The comparative analysis of the two models in terms of detecting growth stages will help to determine the model that the farmers can rely on most in crop care and harvesting.

To sum up, this work discusses the positive aspects of agriculture that technological advancements [13] can bring to pomegranate growing and how it will limit the extent [14] [15] of human labor and support green approaches. With the implementation of machine learning, the agricultural sector will be able to tackle the issue that has always plagued the world- the possibility of producing food for the ever-growing population of the earth, but without excess production and wastage of resources.

2 LITERATURE REVIEW

The technology of object detection has quite recently attained significance in the agricultural sector and it has made it possible to mechanize most of the activities in the field of agriculture such as the management of crops, estimation of yield, and harvest scheduling. The existing practices of identification and monitoring of growth stages of cultivated fruits and vegetables such as pomegranates were more tedious, impartial, and dependent on mankind. The machine learning (ML) and deep learning (DL) approaches, however, have completely changed these scenarios by providing automation and better precision. Consequently, Convolutional Neural Networks (CNNs) and object detection systems like YOLO [16] have achieved significant popularity due to their ability to deliver real-time performance and high accuracy, rendering these systems beneficial in agricultural applications.

2.1 Related Work

Detecting small objects, like buds and early fruit stages of pomegranates, poses a considerable challenge in agricultural applications. Many existing models face difficulties in maintaining accuracy, particularly when objects are small or images are taken in complex settings with varying lighting and background conditions. Recent advancements in YOLO architectures, including the incorporation of attention mechanisms and the implementation of lightweight backbones, have improved the detection of small objects such as buds and flowers. Because of these enhancements, YOLOv5 and YOLOv8 are ideal for monitoring the stages of pomegranate growth in a variety of environmental conditions. The most relevant approach for our research can be found in the first two referenced papers.

In this paper authors present [17] YOLO-Granada, a novel YOLOv5-Based lightweight pomegranate growth recognition system whose primary aim is to improve the detection performed by the system and reduce the time taken in manual orchard management. The model employs ShuffleNetv2 as a Feature Extraction Backbone, thus using grouped convolution and channel shuffle to increase channel interaction while decreasing computation. Further, the Convolutional Block Attention Module (CBAM) is added to highlight prominent features increasing the accuracy of detection. It is noteworthy that YOLO-Granada has an average of 0.922 in accuracy which is lower than that of YOLOv5s which is 0.929 but it also has a 17.3% speed improvement, and less model size, parameters, and floating-point operations. The model is capable of detecting 8.66 images in a second which made possible the real time application. An Android application was also created in the course of the study that would be capable of detecting pomegranates in real-time with the use of Nihui CNN framework, therefore proving useful for smart pomegranate orchard management incorporating advanced technology, that can also serve as inspiration to agriculture neural network designs.

The research presented in [18] focuses on the development of TP-YOLO, a high-performing and portable detection approach based on YOLOv8s that is applied for pomegranate thinning with the use of a picking robot in challenging environments. With the aim of improving the efficiency of the models, the main architecture of YOLOv8s is rewritten using ShuffleNetV2 and in the neck standard convolutions are substituted by depth-wise separable ones. Recognition accuracy is enhanced by integrating the SE attention mechanism into ShuffleNetV2's residual structure. Trained on a self-built pomegranate dataset, TP-YOLO achieves a mean average precision (mAP) of 94.4%, a model size of 1.9 MB, and 8.5 GFlops. The algorithm reduces the number of parameters by 67.9% without compromising accuracy, laying the groundwork for intelligent automation in pomegranate harvesting.

Within the bounds of this research, the authors applied [19] a YOLO-v7 architecture for accurate detection of the pomegranate locations and further growth stages to enhance the crop harvest in the orchards. The dataset comprises 5,857 images of five developmental stages (Ripe, Mid-growth, Early-fruit, Flower, and Bud) which is partitioned into training validation and test datasets. Performance on the validation set (1,105 labels) yielded recall, precision, mAP@0.5, and mAP@0.5:0.95 scores of 0.873, 0.894, 0.939, and 0.822, respectively. The test set (1,109 labels) showed improved scores of 0.888, 0.916, 0.943, and 0.824, even with challenges detecting small labels.

The purpose of the research is [20] to use deep learning and hyperspectral imaging for detecting healthy pomegranates without degrading their quality. Healthy pomegranates were obtained and hyperspectral images were taken prior to and following freezing the samples for two months. This dataset was developed and has 40% of the images containing frozen pomegranates while 60% consisted of healthy pomegranates. The frozen class data was enhanced owing to class imbalance. Image analysis for this research was conducted using deep learning models; ResNeXt, ResNetX, ResNetY, EfficientNetV2, Vision-Transformer, and SwinTransformer. Accuracy for all models exceeded 99% with EfficientNetV2 posting the finest results of all accuracy, precision and recall scores posting 0.9995 F1 Score with very few false positives.

The research is centered on identifying the growth stages of pomegranate plants [21] and especially focuses on the application of the transfer learning-based CRnet approach. The model studied 5,857 images which were labeled into five growth development stages including Bud, Early-Fruit, Flower, Mid-growth, and Ripe stages whereby the model learns spatial features that are fastened by a random forest classifier in order to develop another probabilistic feature set. This Method achieved 98% accuracy which was better than other conventional machine learning approaches such as CNN, KNC, GNB, and LR. This system promotes better management of crops thus increasing the total production while minimizing other threats like pests and diseases by allowing detection at the early stages.

This research paper [22] provides a solution for identifying healthy fruits from unhealthy ones based on color, number of spots, and shape using refined machine learning techniques. The group assembled a combo model that combines CNN and LSTM systems after searching through a database containing 6519 fruits. Convolutional Neural Networks (CNNs) deep extract features, while the classification of these features is performed by Long Short-Term Memory (LSTM) networks using the given features. The results showed that the developed system was successful with an accuracy of 98.17%, specificity of 98.65%, sensitivity of 97.77%, and an F1 score of 98.39%. The novelty here is the increased sensitivity in disease detection as a disease is incorporated in the system even at its early onset where other algorithms mostly fail. Deep learning assumes away such mistakes thereby improving the accuracy of predictive analysis.

An important work we reviewed [23] This paper describes our dataset which contains 5857 images and they all are annotated, pre-processed and structured by the author. Our work which based on this paper.

Table 1. Authors' Conceptual Methodology Findings

Authors	Concept	Method	Findings	Gaps
Jifei Zhao et al.	YOLO-Granada for pomegranate	ShuffleNetv2, CBAM, optimized for	92.2% accuracy, 17.3% faster, detects 8.66 imag-	Needs better small object detection.

(2024) [17]	growth stages	Android	es/sec, 50% model/computation reduction	
Yurong Du et al. (2024) [18]	TP-YOLO for robotic pomegranate thinning	YOLOv8s, ShuffleNetV2, SE attention, depth wise separable convolution	94.4% mAP, 1.9 MB model, 8.5 GFlops, 67.9% parameter reduction	Needs testing in complex environments/other fruits
Mehmet NERGİZ (2024) [19]	YOLO-v7 architecture to detect pomegranate locations and growth stages, improving harvest management.	Dataset of 5,857 images covering five growth stages (Ripe, Mid-growth, Early-fruit, Flower, Bud). Validation and test datasets used.	Validation: Recall 0.873, Precision 0.894, mAP@0.5 0.939, mAP@0.5:0.95 0.822. Test: Improved scores (Recall 0.888, Precision 0.916, mAP@0.5 0.943, mAP@0.5:0.95 0.824).	Challenges in detecting small objects remain.

With the mention of accuracy, speed, and model efficacy, **Table 1** Concisely presents recent works on pomegranate detection using various versions of the YOLO model. Still, object detection in small sizes and testing in more challenging situations are among yet unsolved problems.

3 METHODOLOGY

3.1 Dataset Overview.

The research dataset [23] encompasses 5,857 pictures taken of different stages of the pomegranate (Buds, Flowers, Early fruit, Mid growth, and Ripe stages) between May and September of a plantation located in the Henan Institute of Science and Technology, China. The purpose of this dataset which has been compiled by the School of Computer Science and Technology and the Artificial Light Plant Factory at Henan University is to provide resources for research in such fields as machine learning and computer vision concerned with pomegranate growth monitoring. The dataset is useful to the farmers as it is easy to detect any abnormal changes in agronomic conditions and thus, helps control any possible loss in revenue.

3.2 Feature Extraction Yolov5 and Yolov8

Both YOLOv5 and YOLOv8 emphasize the importance of shape, texture, and color components observed within input images depicting various stages of pomegranate development. These identified features further assist in computing bounding boxes for the target objects i.e. different growth stages, and classifying these objects into appropriate categories with high accuracy, thereby aiding in identifying pomegranates at every growth stage such as a bud, flower, early fruit, mid-grown and ripe. Due to advances in technology, YOLOv8's feature extraction process seems to be even more dynamic and comprehensive which renders it less time-consuming and probably more efficient since better approaches are given to small objects and busy backgrounds.

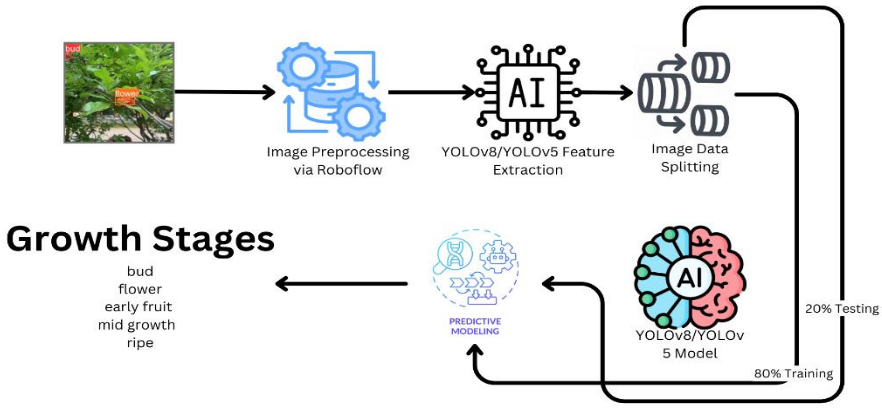

Figure 1. Overall System

The **Figure 1** shows YOLOv8 and YOLOv5 models help spot pomegranate growth stages. This starts with getting the images ready using Roboflow. This means sorting, tagging, and adding more images to train the model better. The pictures show pomegranates at different points: when they're just buds, flowers small fruits growing fruits, and ripe ones. After this prep work, YOLOv8 or YOLOv5 [24] look at the images to find key things that show each growth stage. The team splits these prepped images into two groups: 80% to teach the model and 20% to check how well it learned. The models then learn from the tagged images how to spot and name the different pomegranate stages. Once they've learned, the team tests how well the models can guess the stages. In the end, they check how good the models are by using the test images. This makes sure the models can spot pomegranate growth stages when used later on.

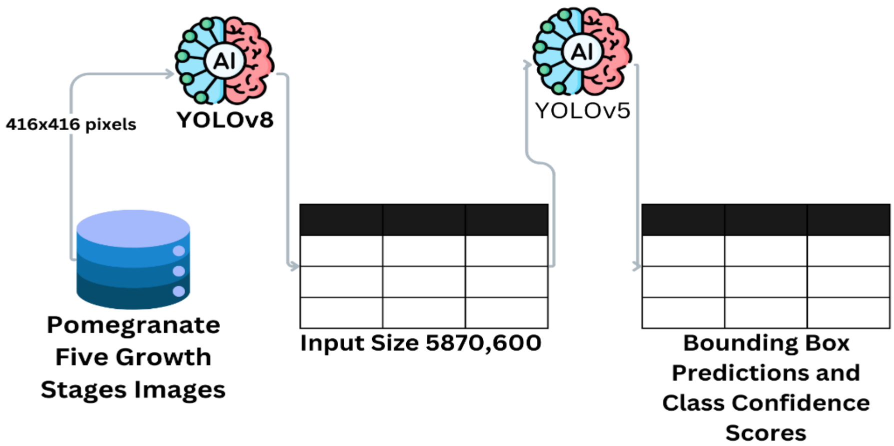

Figure 2.YOLOv8 And YOLOv5

The **Figure 2.** shows the process kicks off with a dataset of 5,870 pomegranate images showing different growth stages (bud, flower early fruit mid-growth, and ripe). To keep things consistent, each picture gets resized to 416x416 pixels before it's fed into YOLOv8 and YOLOv5 models to extract features. These models learn to spot growth by figuring out bounding box predictions and class confidence scores. Both models go through the input images, with [25] YOLOv8 and YOLOv5 checking out the dataset to draw bounding boxes around the important stuff (the pomegranates) and give confidence scores based on how likely the spotted objects match specific growth stages. The models work with an input size of 5870,600 parameters aiming to get good at sorting and predicting the growth stages of the pomegranates. This method gives us a solid way to detect growth stages, which comes in handy for farming and making predictions.

4 EXPERIMETNS AND RESULTS

We use here two object detection model which are YOLOv8 and YOLOv5. In below **Table 2** and **Table 3** describes about our model configuration which can give the idea of the comparison of the model.

Table 2. YOLOv5 Objection model.

Parameters	Values(YOLOV5)
Epoch	60
Image size	416
Batch size	16
Number of images	5857
Layers	182

Parameters	7257306

Table 3. YOLOv8 Objection model.

Parameters	Values (YOLOv8)
Epoch	60
Image size	416
Batch size	16
Number of images	5857
Layers	168
Parameters	11127519

4.1 YOLOv8

YOLOv8 gives the best result in our analysis here we observe that 0.9 mAP50 and 0.894 of precision and 0.832 of Recall.

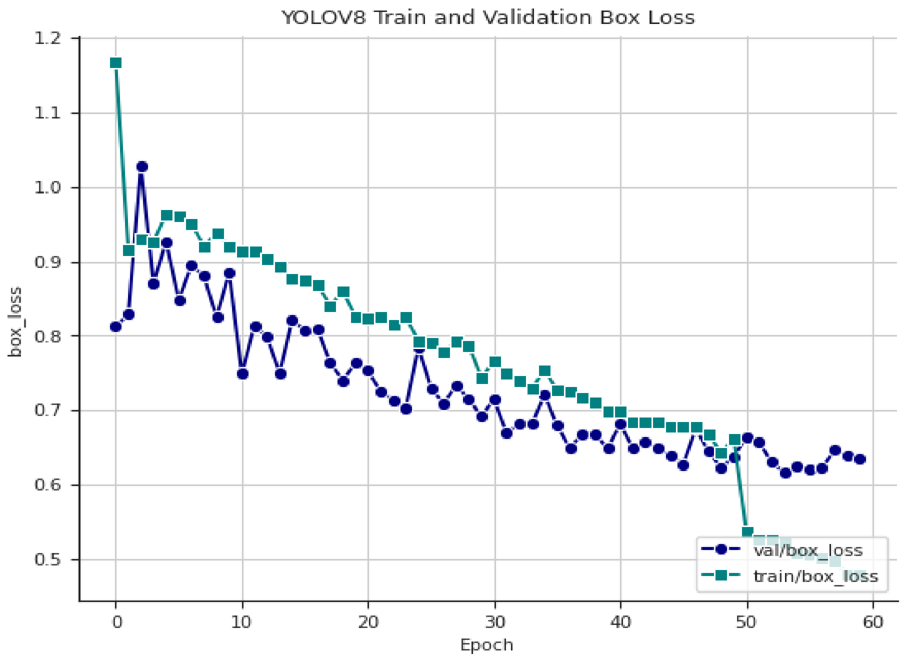

Figure 3. YOLOv8 training and validation box loss, converging near epoch 50.

The **Figure 3** illustrates the box loss trend for both training and validation sets during 60 epochs using YOLOv8. A steady decrease in loss is observed, with the validation and training losses converging near epoch 50, indicating improved model performance and reduced overfitting.

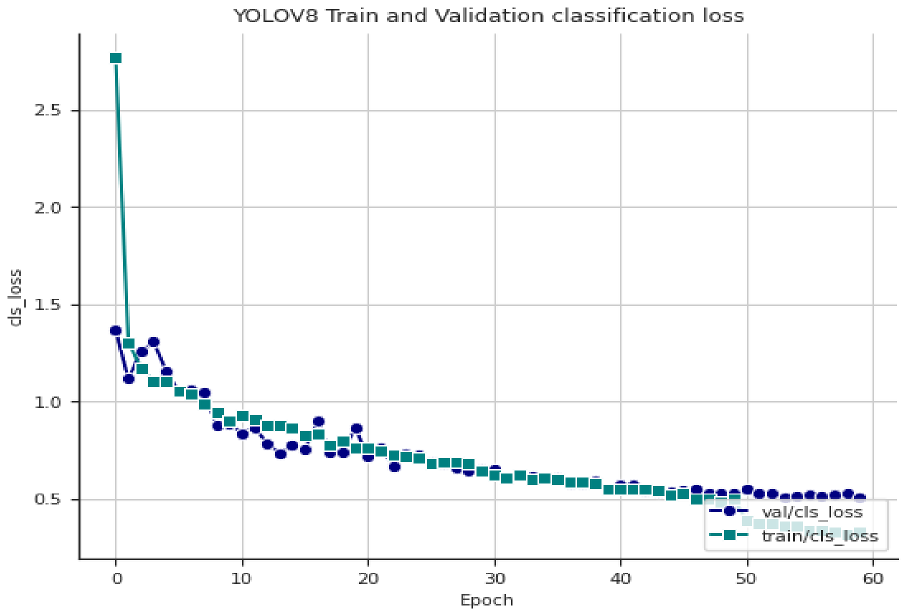

Figure 4. YOLOv8 classification loss for training and validation, converging near epoch 50

The **Figure 4** demonstrates a sharp decline in both training and validation classification loss, with losses stabilizing around 0.5 after 50 epochs, indicating successful model learning and reduced classification errors.

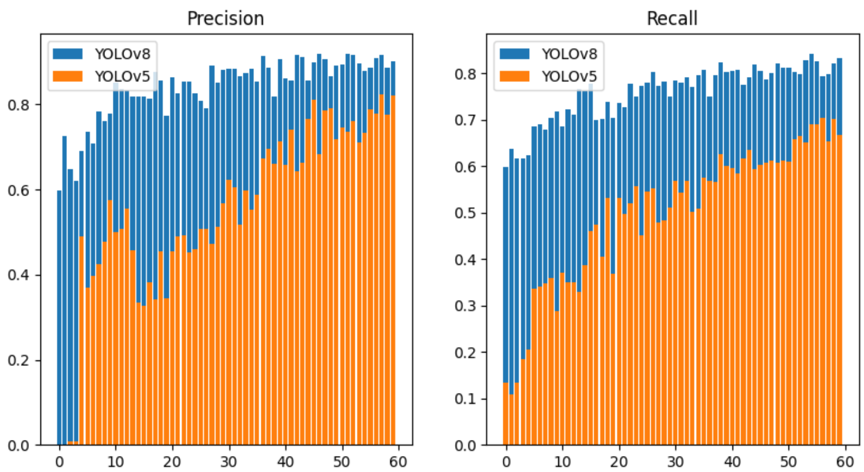

Figure 5. Precision Of YOLOv8 And YOLOv5

From the **Figure 5** we see that every epoch the yolov8 was far better than yolov5. So, the detection of growth stage of pomegranate with yolov8 is more accurate than yolov5.

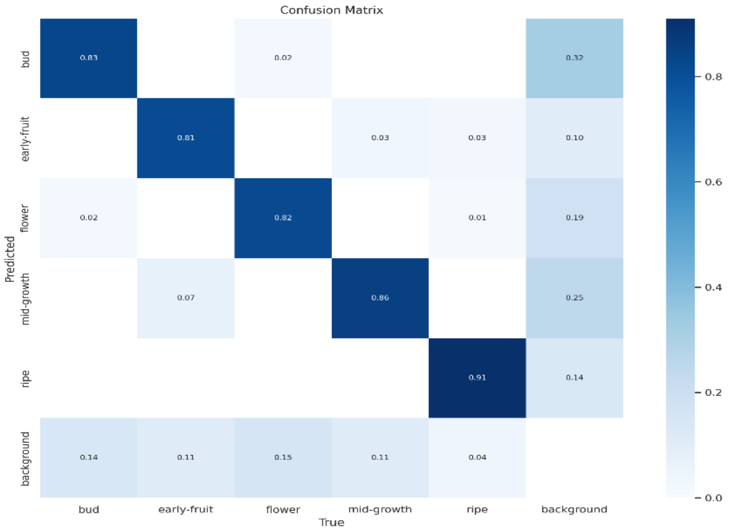

Figure 6. Confusion Matrix

The **Figure 6** the confusion matrix shows the performance of a classification model across six categories: bud, early-fruit, flower, mid-growth, ripe, and background. The diagonal values indicate correct predictions, with the model performing best in predicting "ripe" (91%) and "bud" (83%). Misclassifications are more noticeable between "background" and other stages like "bud" and "ripe."

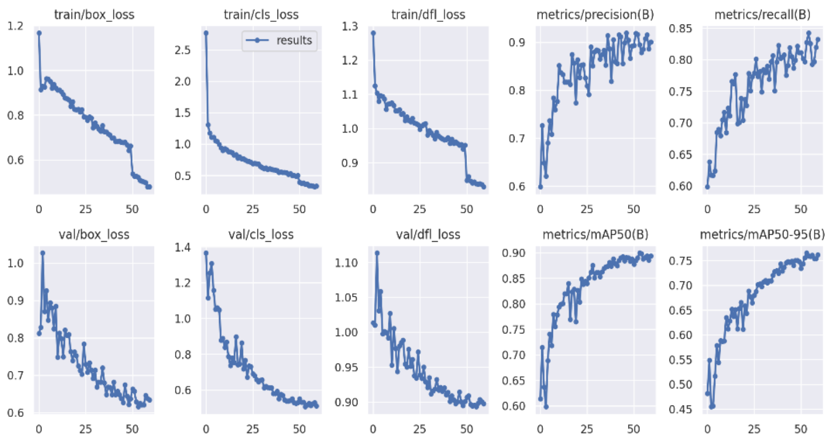

Figure 7. Result

The **Figure 7** displays various performance metrics of a model during training and validation over 50 epochs. The losses (box, classification, and distributional focal loss) decrease steadily, while the metrics (precision, recall, mAP@50, and mAP@50-95) improve, indicating model convergence and enhanced performance.

While both our research and the research conducted by Mehmet Nergiz, entitled "Detection and Classification of Pomegranate Fruits Growing in Stages Based on YOLO-v7", [19] concerns about deep learning-based classification of pomegranate growth stages, this section outlines a comparison of the results from both studies. The following section contains a summary of the performance metrics, emphasizing the differences and similarities in results obtained by both studies.

Table 4. Comparative Analysis of YOLOv7, YOLOv8, and YOLOv5 for Pomegranate Growth Stage Detection

Metric/Aspect	YOLOv7	YOLOv8	YOLOv5
Model Architecture	YOLOv7	YOLOv8	YOLOv5
Dataset	5,857	5,857	5,857
Training Images	4,685	4,686	4,686
Validation Images	585	586	586
Test Images	587	587	587
Precision (%)	89.4%	89.4%	77.2%
Small Object Detection	Bug	YOLOv8 had better small object detection	YOLOv5 had difficulty detecting small
Confusion Matrix Insights	High true positive rate for "ripe" (0.986); 31% of buds misclassified as background [26]	YOLOv8 performed well, but struggled with early-fruit and mid-growth stages	YOLOv5 misclassified small objects more frequently than YOLOv8 [28]
Speed and Real-Time Capability	Fast, optimized for real-time object detection	Optimized for mobile hardware and real-time applications [27]	Slightly slower than YOLOv8 and YOLOv7
Best Performing Classes	Ripe, Early-fruit	Ripe, Mid-growth	Ripe, Mid-growth
Worst Performing Classes	Bud	Early-fruit	Bud, Early-fruit

The **Table 4** provides a detailed comparison of the results from the YOLOv7 model (existing paper) with the YOLOv8 and YOLOv5 models (our study). The comparison covers key performance metrics such as precision and challenges in detecting small objects, highlighting the strengths and weaknesses of each model in detecting different growth stages of pomegranates.

5 Limitation

Even though pomegranate growth stages were successfully detected, [26] There were still some limitations within the scope of the YOLOv8 and YOLOv5 models. The predictions, and hence the detection of such stages, were affected by the imbalanced classes present in the developed dataset, where some stages had very few images. Furthermore, the training of the model was based on a particular region and period and therefore generalized results cannot be expected for other climates or regions without retraining the model.

The possible overfitting that could arise from the small dataset was a threat to the model. Generalization could then be improved by the use of cross-validation and data augmentation. The “black box” nature of the models was another con in that it was difficult to understand the predictions as they were important for farmers who had to make decisions.

Things such as soil and irrigation will affect the growth of pomegranate trees but it’s difficult to include them into one dataset so retraining after some time will be a must for the model to perform well. Another challenge is regarding scalability since the implementation of the models in a big real-time agricultural application may be power intensive in terms of computation resources.

Finally, in addition to these potential limitations, the present research covered five growth stages but not all intermediate stages which practically occur in farming, thus impacting accuracy in practical use. By combating these challenges—class imbalance, overfitting, interpretability, and scalability—the quality of prediction could be enhanced.

6 Future Work

To increase the strength and precision of the model, the pomegranate dataset should be augmented with additional developmental stages and climatic variations in future studies. Performance with few data can be improved by employing transfer learning, while performance in changing conditions can be enhanced by using ensemble learning, which is combining the output of several models. [27] The use of attention mechanism may assist in reducing growth stage detection errors by directing the model to salient parts of an image. Utilization of optimization algorithms such as AdamW or RMSProp is another area that could enhance speed and performance of the training. These approaches – transfer learning, ensemble models, attention mechanisms, and advanced optimizers – could enhance the models’ precision with respect to a wider range of agricultural practices and their applicability.

7 Conclusion

Pomegranate growth stages were detected using two deep-learning models, YOLOv8 and YOLOv5, which were validated in this study. The models were trained with 5,857 images and five phases, namely budding, flowering, early fruiting, medium growth, and maturity were identified. Both of the models were examined in terms of accuracy and computation efficiency. The results indicate that pomegranate growth stages can be effectively identified by both YOLO version 8 and Yolo version five, which perform good in precision, recall and mean average precision (mAP).

YOLO8 is a lightweight version of the neural network model that allows mobile real-time implementation on devices with low system resources. Yolo version five requires considerably more resources, and tamer faster than the previous version of the neural net. It is worth mentioning both models are important in agriculture.

The method is not only restricted to the pomegranate and extends to other crops benefitting the farmers when it comes to growth stages management, yield estimation, and harvest timing. Thus, aiding in improving the crop management and effectiveness of the sector as a whole.

In summary, the growth stages of pomegranates were successfully detected using both YOLOv8 and YOLOv5 models. The future work will involve more complex modifications of the mentioned models, inclusion of weather and soil data and enhancement of tracking of various plants in order to improve precision agriculture.

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