VFAST Transactions on Software Engineering
https://vfast.org/journals/index.php/VTSE@ 2024, ISSN(e): 2309-3978, ISSN(p): 2411-6246
Volume 12, Number 2, April-June 2024 pp:250-259

Efficient Real-Time Detection of Plant Leaf Diseases Using YOLOv8 and Raspberry Pi

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Keywords: *Plant disease detection, Deep Learning, YOLOv8,Wheat disease, apple disease*

Journal Info:
Submitted: April 19, 2024
Accepted: June 25, 2024
Published: June 30, 2024

Abstract The utilization of deep learning-based models for automatic plant leaf disease detection has been established for many years. Such methods have been successfully integrated in the agriculture domain, aiding the swift and accurate identification of various diseases. However, the unavailability of annotated data, the variability of systems, and the lack of an efficient model for real-time use remain unresolved challenges. The goal of this work was to develop a deep learning-based model for crop disease detection and recognition system for real-field scenarios. For this, we trained lightweight versions of the YOLOv5, YOLOv7, YOLOv8 and compared their detection performance. Experiments were carried out on a self-collected dataset containing 3136 real-field images of apples (healthy and diseased) and 567 images of PlantDoc dataset. Results revealed that the prediction accuracy of YOLOv8 was superior to others on AdamW optimizer. The results were further validated by deploying it on Raspberry Pi 4.

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DOI: 10.21015/vtse.v12i2.1869

1 Introduction

Agriculture has been a fundamental source of nutrition and livelihood for humanity since the dawn of civilization [1]. Pakistan's agriculture sector [2] is central to the economy, contributing 18.9 percent to the GDP and employing 42.3 percent of the labor force. Additionally, agriculture is a significant source of foreign exchange revenue, further underscoring its importance. The agricultural sector, encompassing crops, fruits, and vegetables, is the cornerstone of the nation's economy.

However, outdated agricultural methods and inefficient technology utilization have severely impacted both local productivity and international trade [3]. Pathogenic infestations [4] further magnifies this issue, leading to diminished yields of agricultural productivity. Effective management techniques and early diagnosis are crucial for reducing crop disease outbreaks and financial losses [5]. Research and innovations in integrated pest management, precision agriculture, and disease-resistant crop types are essential to prevent crop diseases and maintain a sustainable food supply.

Crop diseases seriously harm the agricultural sector, lowering food supply, diminishing yields, and threatening economic stability. Crop illnesses can reduce yields by 10% to 100%, based on the kind and severity of the infection, as reported by the Food and Agriculture Organization (FAO) [6].

To limit losses and preserve sustainable agricultural output, crop diseases must be addressed using integrated pest management techniques, robust crop types, and early detection technologies [3]. Human-based conventional techniques are unreliable because diseased symptoms are similar and overlapping. Additionally, the identification is labor-intensive and time-consuming [7]. Hence, artificial intelligence-based systems [8] have become increasingly prevalent to mitigate real-field challenges and effectively detect and classify plant diseases. Convolutional Neural Network (CNN) based techniques have been extensively used in recent years for various agricultural applications [8], including plant disease classification [9], weed identification [10], fruit grading [11], yield prediction [12], and early plant stress management [4]. Although the use of deep learning techniques is ever-increasing, there is a growing need to localize diseased symptoms and subsequently classify them accurately. The advent of models such as Faster R-CNN, SSD, and YOLO has developed the field of detection, making these tasks more efficient and precise [13].

The significance of accurate and timely plant disease detection cannot be denied. However, the variability of symptoms [9], complex backgrounds, varying lighting conditions, and the lack of real-field datasets make the task notably more challenging for researchers [14]. Researchers have incorporated conventional image processing-based, color-texture information to identify diseased symptoms present on plants [15]. Convolutional Neural Networks (CNNs) and AI-based methods are being employed to automatically learn and extract deep features from image datasets [4], which can then be used for prediction and classification tasks. Models like EfficientNet [16], MobileNet [17], AlexNet [18], VGG, and ResNet are particularly notable for their ability to provide high accuracy while functioning as end-to-end models. These models not only enhance prediction accuracy but also streamline the process by learning features automatically. Moreover, their ability to handle the complexity of various datasets makes them invaluable in the field of image-based classification.

Object detection methods have evolved to enhance weed identification, pest control, and plant disease detection [19]. Researchers encounter challenges in locating and classifying stress types in real-world scenarios [14]. Robust and accurate models trained on large datasets show significant potential for agricultural applications. They can be deployed on hardware platforms or embedded systems to create automated plant disease detection systems [20]. Researchers worldwide strive to develop accurate and efficient models for localizing and classifying diseased parts in images. For instance, Saleem et al [21] trained and fine-tuned various meta-architectures like SSD, RFCN, and Faster RCNN to detect 26 diseased and 12 healthy plant parts, achieving a 73.07% training accuracy for the SSD model with the Adam optimizer.In another study [22], tomato fruit diseases were detected using a 15-layer Single Shot Detector (SSD). The results demonstrated superior performance compared to SSD with VGG16, VGG19, and ResNet backbones.The authors [23] used a novel model using deep block attention along with SSD to identify disease and severity symptoms. The performance of this method was compared with YOLOv4, Faster RCNN, and YOLOv3, showing improved results on the PlantVillage dataset.

To assist farmers in implementing real-time plant disease detection systems, Gajjar et al., [24] explored using a CNN model combined with SSD to detect and localize plant diseases. These models were deployed on embedded hardware, achieving a disease classification accuracy of 98.66% and demonstrating robust performance on the test dataset with the proposed deployable system. in the quest of better accuracy performance in challenging field conditions Li.et al.,[25] proposed model enhanced the performance of YOLOv8s by incorporating the GhostNet triplet algorithm. This simplified architecture resulted in improved accuracy, along with a significant reduction in model complexity and size. Consequently, the proposed model is deemed suitable for practical deployment. In another recently proposed work [26] a YOLOv8-based model achieved improved accuracy, with a performance of 89.9% on a self-collected dataset using α*EIOU* loss function. The examination of recent methodologies guided us to utilize YOLO-based models for our datasets and evaluate their performance on Raspberry Pi-based systems. This approach aims to assess the effectiveness and efficiency of YOLO models in real-time plant disease detection within the constraints of embedded hardware. Hence we used YOLOv8 model to detect and localize wheat and apple leaf disease in field and plain background.

The major contributions of our proposed work include:

- Collection and annotation of a diverse set of diseased plant images from both real-field and controlled environments. We present an apple disease dataset sourced from PlantVillage and subset of PlantDoc dataset.
- Training of the YOLOv8 model under various train-test settings and training epochs to achieve optimal results.
- Deployment of the trained model on a Raspberry Pi 4 to evaluate its performance in real-field detection scenarios.

The rest of this paper is organized as follows: Section 2 describes the proposed methodology, pre-processing techniques, and a dataset discussion. Sections 3 and 4 present the experimental results and conclusions, respectively.

2 Methodology

The overall procedure adopted in this study is illustrated in Figure 1. The authors utilized two distinct datasets and applied preprocessing techniques before making them available for model training. Detailed information is provided in Section 2.1. Subsequently, various versions of YOLOv8 were trained to accurately and quickly identify and localize plant diseases in the apple and Plantdoc datasets. After analyzing the results, the optimal model was deployed on a Raspberry Pi 4. .

2.1 Dataset Description

For training, we use the following two datasets discussed in detail below:

2.1.1 Apple disease dataset

The dataset is a subset of the PlantVillage dataset [27]. It contains 3,163 images of healthy and diseased apple leaves. The diseased apple classes are

- Apple scab is a fungal disease and its symptoms appears on leaves, twigs, and fruits. Dark velvty spot appears which later forms irregular lesions and also cause leaf discoloration as shown in Figure 2 (b).
- Apple cedar rust is also a fungal infection that initiates with pale yellow and reddish circular lesions on the leaf surface and gradually enlarges into orange-yellow spots as shown in Figure 2 (c).
- Apple Black rot is caused by a fungal pathogen that begins with specks on leaves and later develops into frog-eyed brownish and reddish lesions as shown in Figure 2 (d).

The number of images per class is listed in Table 1.

Table 1. Details of Apple disease dataset

class	Number of images
Apple healthy	1637
Apple scab	630
Apple cedar rust	275
Apple Black rot	621
Total	3163

2.1.2 PlantDoc Dataset

PlantDoc [28] is a real-field benchmark dataset used in plant disease detection. We have used a subset of this dataset. The augmented dataset we have used in our study contains 567 images of 7 classes of apple rust, apple scab, cherry healthy, bell pepper healthy, bell pepper leaf spot, blueberry healthy leaves, and apple healthy The snapshot of the dataset used is shown in Figure 3.

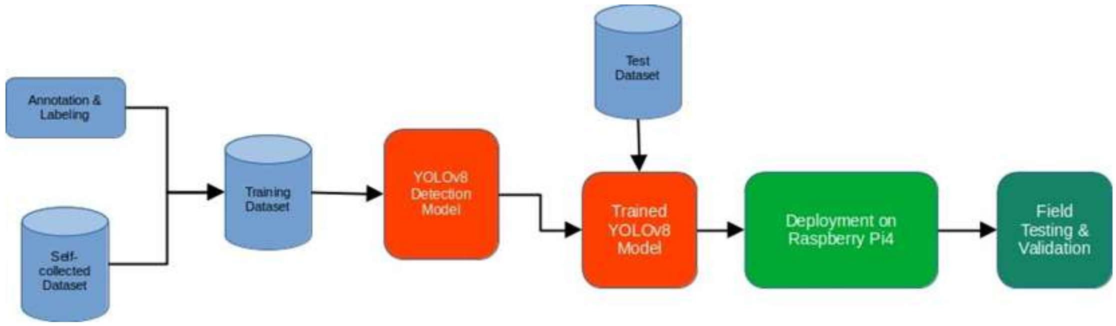


Figure 1. Block Diagram of Proposed System

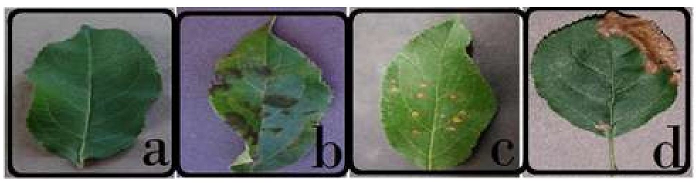


Figure 2. Snapshot of Apple disease Dataset. (a) Apple Healthy (b) Apple Scab (c) Apple Cedar Rust (d) Apple Black Rot

Figure 3. Snapshot of 8 classes of plantdoc dataset (a) Apple rust (b) Apple Scab (c)Cherry healthy (d) bell pepper healthy (e) bell pepper leaf spot (f) blueberry healthy (g) Apple healthy

Apart from healthy leaves, we included disease classes of apple scab and apple rust in the apple disease dataset. Additionally, we incorporated bell pepper leaf spot, a fungal disease characterized by water-soaked lesions on both the upper and lower sides of the leaf, as shown in Figure 3 (e). The number of images per class is listed in Table 2.

2.2 Dataset Labelling & Augmentation

The labeling of images for class assignment was performed using Roboflow. After correct annotation and label assignment, an auto-orient operation was applied during preprocessing. All images were resized to 640×640. Various types of data augmentation were employed to triple the size of the training dataset. These augmentations included vertical and horizontal flips, rotations of *pm*15%, and brightness adjustments of *pm*15%. Both datasets were divided into train, validation, and test parts on varying ratios to analyze the best results.

Table 2. Details of PlantDoc dataset

class	Number of images
Apple rust	89
Apple scab	87
Cherry healthy	56
Bell pepper healthy	56
Bell pepper leaf spot	91
Blueberry healthy	105
Apple healthy	83
Total	567

2.3 YOLOv8 model

YOLOv8, the latest YOLO-based target detection algorithm, is a unified framework for training models in target detection, instance segmentation, and image classification. Compared to its predecessors, YOLOv8 supports operations on various hardware platforms with enhanced speed and accuracy. The model architecture comprises three main components: Backbone, Neck, and Head as shown in Figure 4. The Backbone uses C2f and SPPF structures to maintain a lightweight network and provide rich gradient flow information. The SPPF structure enhances the receptive field through various max-pooling layers. The Neck adopts the up-sampling convolution structure to retain feature information, while the Head employs a decoupled-Head structure and an Anchor-Free

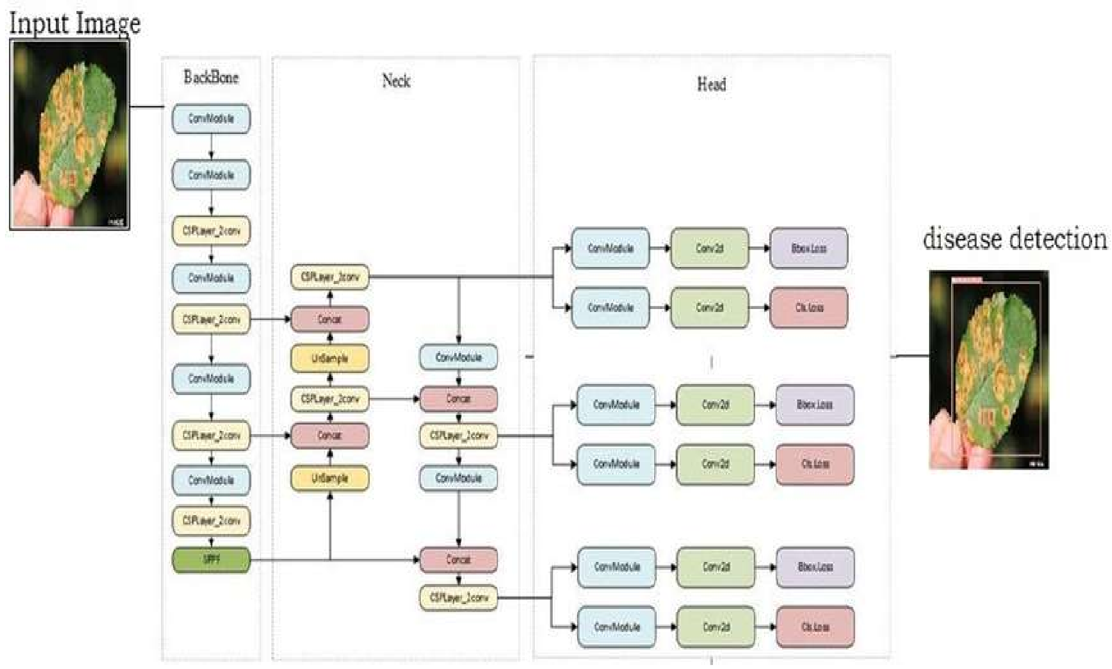


Figure 4. Plant disease detection model

Table 3. Training performance of the YOLOv8s model on the Apple Disease dataset with different train-test splits

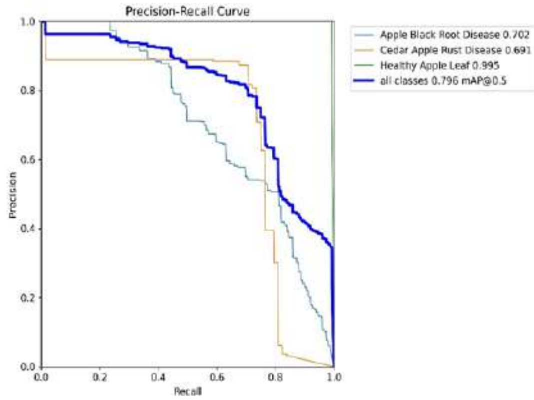
epochs	train-val-test ratio	Precision(P)	Recall(R)	mAP@50%
50	80-10-10	0.841	0.765	0.796
50	70-20-10	0.79	0.745	0.78
50	60-30-10	0.785	0.73	0.746
50	50-40-10	0.769	0.686	0.706

Table 4. Training performance of the YOLOv8s model on the PlantDoc dataset with different train-test splits

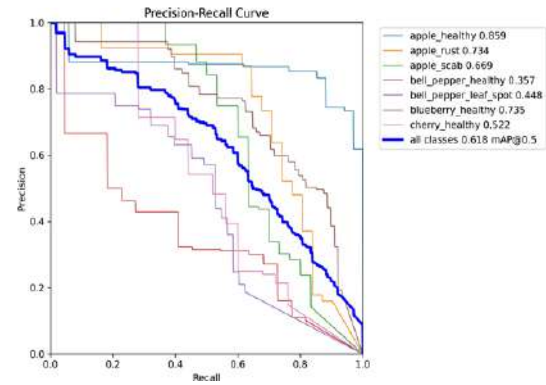
epochs	train-val-test ratio	Precision(P)	Recall(R)	mAP@50%
50	70-20-10	0.672	0.57	0.631
50	60-30-10	0.63	0.54	0.601
50	50-40-10	0.60	0.51	0.58

Table 5. Training performance of the YOLOv8s model on the PlantDoc & Apple disease datasets with different optimizers

optimizer	learning rate	momentum	mAP@50 Plant Doc	mAP@50 Apple disease
AdamW	0.000909	0.9	0.631	0.796
Adam	0.001	0.95	0.56	0.69
SGD	0.001	0.90	0.58	0.68
RAdam	0.01	0.937	0.605	0.75
NAdam	0.05	0.87	0.61	0.758

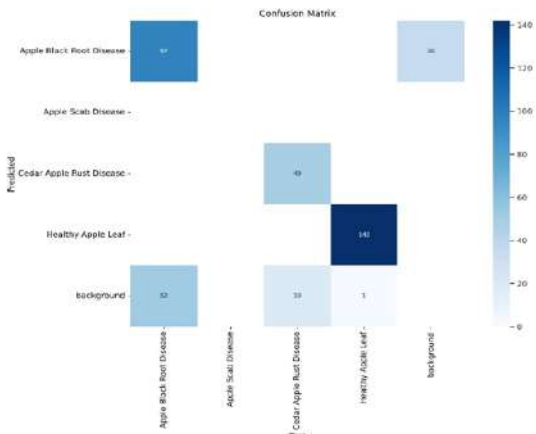


(a) Apple Disease dataset

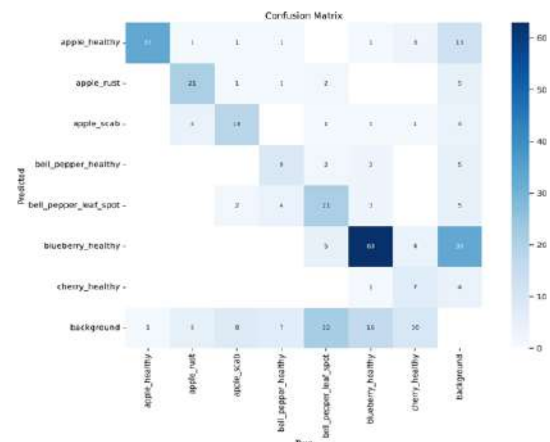


(b) PlantDoc dataset

Figure 5. Precision Recall Curve



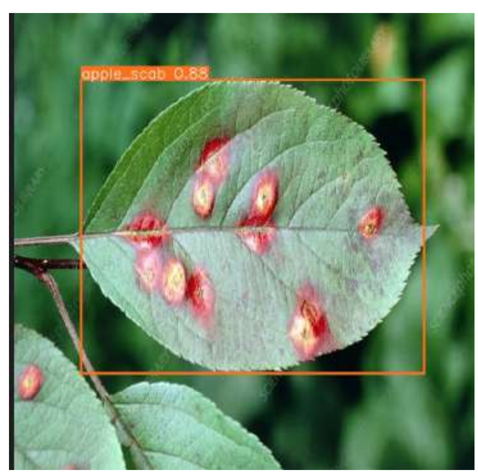
(a) Apple Disease dataset



(b) PlantDoc dataset

Figure 6. Confusion matrix on training dataset

(a) detection of healthy apple leaf image showing im- proved confidence score



(b) detection of apple scab with improved confidence score

Figure 7. Detection Results on test dataset

strategy to improve convergence speed. The head incorporates the fused features from the neck to generate a bounding box and predict class.

YOLOv8 offers five model versions with varying sizes and complexities. The YOLOv8n model is compact and fast but less accurate, while YOLOv8x provides the highest detection accuracy at the expense of speed. This study focuses on real-time plant disease detection and localization on embedded devices like Raspberry Pi. After evaluating each YOLOv8 version, YOLOv8s was chosen for its optimal balance of computational cost and detection accuracy.

2.4 Experimentation

The experimentation was conducted on Google Colab with access to a T4 GPU, utilizing a system equipped with a Core i3 processor and 8GB of RAM. The model was trained on two annotated datasets mentioned in section 2.1 downloaded in TXT format, using YAML annotations for data labeling. During the fine-tuning process, various learning rates were tested, and multiple optimizers were experimented with to determine the optimal settings. Additionally, different train-test split ratios were employed to enhance detection accuracy and convergence rates. The batch size was set to 16, and the training process was carried out over 50 epochs. In the first instance, we analyzed the training detection accuracy on mAP(mean accuracy precision) metric. While Adam and SGD optimizers have been popular choices among researchers, we explored and found that AdamW offers significant advantages. AdamW [29] is a stochastic optimization method that modifies the typical implementation of weight decay in Adam by decoupling weight decay from the gradient update. This decoupling allows for better control over regularization, leading to improved convergence and performance.

3 Results

During the first set of experiements, we varied train-validation and test splits of both datasets and analyzed that better precision and recall values were observed on higher training ratio as compared to validation and test images. The same can be observed from Tables 34.

In the later stages of the experiment, we applied different optimizers with their default learning rates and momentum settings to both datasets to evaluate the model's accuracy performance. The best performance was observed with the AdamW optimizer for both the PlantDoc and Apple disease datasets. For comparison, we computed mAP values using Adam, SGD, NAdam, and RAdam optimizers, as shown in Table5

The model performance can be analyzed by showing the precision-recall curve in Figure 5

A classifier performance in any multi-class problem can be analyzed from the confusion matrices. As can be seen in Figure 6 (a) the healthy apple is the most truly detected class with no false positives and false negatives.

The detection results on test datasets are shown in Figure 7. The detection results are obtained on YOLOv8s model with parameter settings mentioned in Section 2.

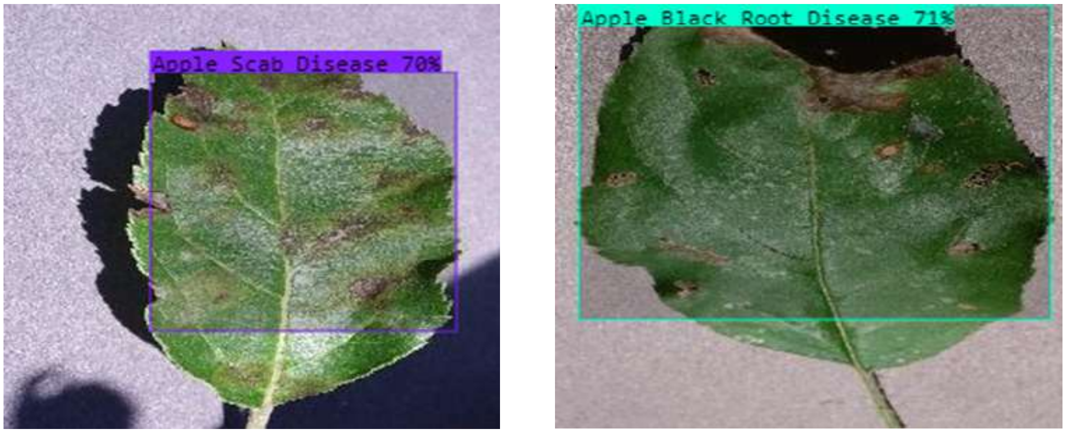
To validate the efficiency and efficacy of the model its detection performance was also compared with other state-of-the-art models on training datasets as shown in Table 6. Table 6 shows that the YOLOv8s model shows superior performance than other models in terms of training accuracy.

3.1 Raspberry Pi4 implementation & detection results

For our trained model to run on Raspberry Pi4 inference docker was installed first and then used to deploy the model. The model is run on Pi's CPU. Roboflow API is installed in the Pi as its CPU contains no models. The CPU of Raspberry Pi4 is 1.8GHz Broadcom, Cortex-A72 64Bit which shows better inference performance than Raspberry Pi5 on the YOLOv8 model. After importing the model from Roboflow on ready-to-use Raspberry pi 4 model B, here are the results of Raspberry Pi object detection are shown in Figure 8.

Author Contributions

Basit Ahmad: Conceptualization, Methodology, Software **Serosh Karim Noon**: Supervision, Writing-Original draft preparation, **Talha Ahmad** Experimentation, **Abdul Mannan**: Data Curation, Investigation, Experimentation **Noman Ijaz**: Writing- Reviewing and Editing **Muhammad Ismail**: Software, Validation.**Tehreem Awan**Results, Reviewing.



(a) (b)

Figure 8. Raspberry Pi4 inference on random images

Table 6. Comparison of mAP@50 of different models on training dataset

Model Name	PlantDoc(mAP@50)	Apple Disease (mAP@50)
FasterRCNN	0.51	0.65
YOLOv5tiny	0.50	0.695
YOLOv5s	0.57	0.77
YOLOv7s	0.55	0.75
YOLOv8n	0.59	0.75
YOLOv8s	**0.63**	**0.77**

Compliance with Ethical Standards

It is declared that all authors don't have any conflict of interest. Furthermore, informed consent was obtained from all individual participants included in the study.

Funding Information

No funding is used for this project

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