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The Analysis of Architectural YOLOv5 Convolutional Neural Networks for Detecting Apple Leaf Diseases

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Abstract. *Apple cultivation is crucial to agricultural economies, particularly in regions with sub-tropical climates, such as Indonesia, where apple farming is expanding rapidly. However, managing diseases and pests is essential for maintaining optimal crop yields, as they can significantly reduce production. Among the common diseases affecting apple trees are Scab, Black Rot, and Cedar Apple Rust, which primarily impact leaves and threaten the total health of the plant. Therefore, this research aimed to develop an effective model for detecting apple leaf diseases using the architectural YOLOv5 Convolutional Neural Networks (CNNs). The analysis was conducted between November 2022 and February 2023 at the Smart City Information System (SCIS) laboratory, including 120 apple leaf samples collected from Tawangmangu. Additionally, secondary data containing 30 images for each disease category, consisting of Healthy, Scab, Black Rot, and Cedar Apple Rust, were used as a benchmark. The performance of YOLOv5 was evaluated based on several metrics, including Precision, Recall, mAP@0.5, and mAP@0.5:0.95. The results showed that Cedar Apple Rust was the most prevalent disease identified among the samples. YOLOv5 performed exceptionally well in detecting disease symptoms, achieving a Precision score of 0.810, Recall of 0.981, mAP@0.5 of 0.950, and mAP@0.5:0.95 of 0.765 on the test dataset. These results showed that the proposed model was highly accurate and reliable for the early detection of apple leaf diseases, offering significant potential for improving disease management strategies and increasing the efficiency of apple production.*
Keywords: *agriculture; apple leaves; detection; disease symptoms; YOLOv5.*

Type of the Paper: Regular Article.

1. Introduction

Agriculture is the use of natural resources to produce food, industrial materials, and energy sources, as well as to support environmental management. With the use of technology, agriculture and agronomy are not only the same as conventional agricultural science, which focuses on plant use. In general, the use of technology in agriculture is a series of activities aimed at modifying the environment to produce plant or animal products that benefit humans. Despite the significant potential of agriculture, the sector faces numerous challenges, particularly reductions in yield due to attacks by pests and diseases, known as Plant Pest Organisms (PPO). These attacks can be caused by fungi, bacteria, and viruses, which can significantly disrupt agricultural productivity. A practical strategy to address such issues is the early detection of pathogens through the analysis of infected plant leaves [1].

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One important agricultural product is the apple (*Malus sylvestris* Mill), a perennial fruit plant native to West Asia that thrives in sub-tropical climates. In Indonesia, apple cultivation began in 1934 [2], and the country now produces various popular varieties, such as Manalagi, Rome Beauty, and Anna, all known for their high vitamin C and B content [3,4]. However, the cultivation faces various challenges, including pest and disease attacks. Common pests, such as fruit flies and green aphids, along with fungal diseases, particularly Scab, Black Rot, and Cedar Apple Rust, pose significant threats to apple yields [5–7]. Severe cases of these diseases can cause significant declines in production. Additionally, factors such as the increasing age of apple trees and climatic change can cause a decrease in production yields. Without proper management, apple cultivation will continue to experience a decline in yields, negatively affecting farmers' livelihoods. Therefore, the prevention and control of pests and diseases are important for supporting the growth and productivity of apple plants [8].

Scab is a bad problem for apple plants and comes from a fungus called *Venturia inaequalis* G.Wint [9–11]. It makes green spots that turn black later [12]. Black Rot is also bad and causes fruit rot and black marks. Cedar Apple Rust is another problem, and it has orange galls that kind of look like flowers. Knowing about these problems helps prevent crop losses. Farmers need to see symptoms early to know when it is Scab, Black Rot, or Cedar Apple Rust, so they can take preventive measures [13,14].

Convolutional Neural Networks (CNNs) are tools used for detecting disease symptoms. They are a part of Artificial Intelligence. CNNs came from Multi-Layer Perceptron (MLP) models [1,15]. These tools are neural networks with many layers. They are mostly used for image analysis and work in two dimensions [16]. Essentially, CNNs mimic human brain functions, processing inputs through neurons, and hidden layers, as well as producing outputs [17,18]. These machine learning tools have demonstrated remarkable accuracy in large-scale video and image recognition [19,20]. For instance, Google uses CNNs to retrieve house numbers from street-view images. The advantage of the machine learning tools is that they have high sensitivity and specificity in object detection [20,21]. When applied to plant disease detection, CNNs can accurately classify images of apple plants affected by diseases such as Black Rot, Scab, and Cedar Apple Rust, as well as images of healthy leaves. The machine learning tools, trained on thousands of images, have proven effective in achieving high classification accuracy in image recognition [22].

CNNs are currently among the most widely used algorithms for object detection, partially due to their support by frameworks such as Google's TensorFlow. Despite its advantages, the machine learning tools demand significant computational resources, requiring considerable time, extensive datasets, and high-performance hardware [23]. To address these limitations, the You Only Look Once (YOLO) architecture can be integrated to enhance efficiency.

YOLO looks at pixels to find objects using colors and shapes it learned before. It helps to detect and classify object damage fast and accurately [14]. YOLO works with Darknet and Darkflow, which are good for GPUs [24,25]. Joseph Redmon made YOLO in 2015, and it uses CNNs. In 2017, Redmon and Farhadi showed YOLOv2 at a conference, which was better and faster [19]. Later in 2018, YOLOv3 came out, which improved more [26]. YOLOv5 can find three apple plant diseases like Black Rot, Scab, and Cedar Apple Rust [27–29].

This research aimed to develop an effective model to detect apple leaf diseases with YOLOv5 CNNs. The analysis was conducted in Tawangmangu, where a total of 120 apple leaf samples were collected. For comparison, secondary data, comprising 30 images from each disease category, particularly Healthy, Scab, Black Rot, and Cedar Apple Leaf Rust, was also used. The research adopted the mean Average Precision (mAP) error evaluation matrix [30]. It is believed that the method will help in the classification of Scab, Black Rot, and Cedar Apple Rust, potentially preventing crop failure and reducing losses for farmers.

2. Materials and methods

The data used in this research was sourced from secondary images of apple plant leaves available on GitHub at the link https://github.com/lzoran/plant-disease-dataset/tree/master/data. The dataset contained 120 images, categorized into four groups, including Healthy, Black Rot, Scab, and Cedar Apple Rust, with 30 images in each category. The research was carried out between November 2022 and February 2023 at the UTP Smart City Information System (SCIS) laboratory. With the use of CNNs, images were processed to identify and detect disease symptoms accurately. The data collection process followed the steps outlined in Fig. 1.

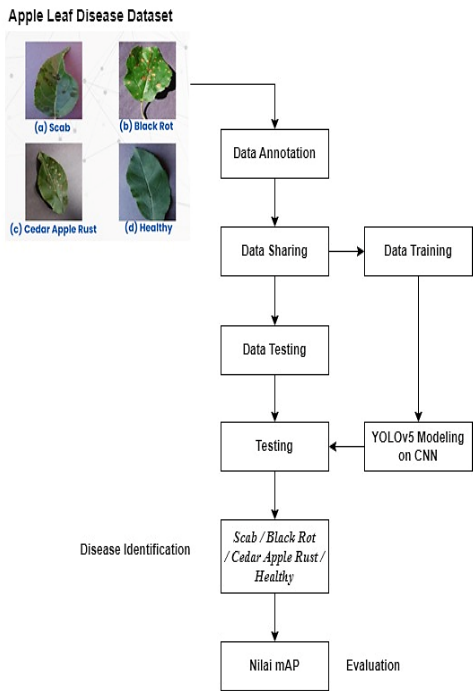

Fig. 1. Stages of YOLOv5 CNN on Apple Leaf Diseases

Identify disease symptoms from each image on apple leaves obtained according to Shurtleff et al. [31].

a. **Data Annotation.** The collected data was processed into the data annotation stage by giving a label to apple leaf images including symptoms of Scab, Black Rot, and Cedar Apple Rust. Data that have been annotated could be divided into training and test datasets.
b. **Data sharing.** The annotated data was grouped into two parts, including training and test datasets. The division of data groups included 70% for training data and 30% for test data. In this stage, the target to be achieved was data with proper distribution.
c. **Modeling YOLOv5 on CNNs**. Modeling used YOLOv5 on CNNs because it had a relatively short time with a high Average Precision, as presented in Fig. 2.

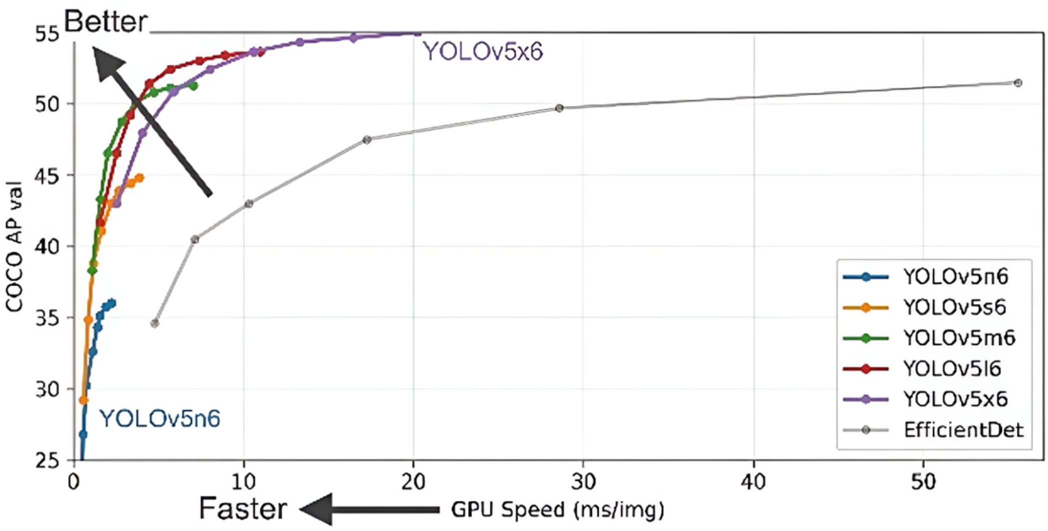

Fig. 2. Comparison of Average Precision YOLO Model

The training data was subjected to YOLOv5 architecture for detecting apple leaf diseases with training labels including symptoms of Scab, Black Rot, and Cedar Apple Rust, as detailed in Fig. 3.

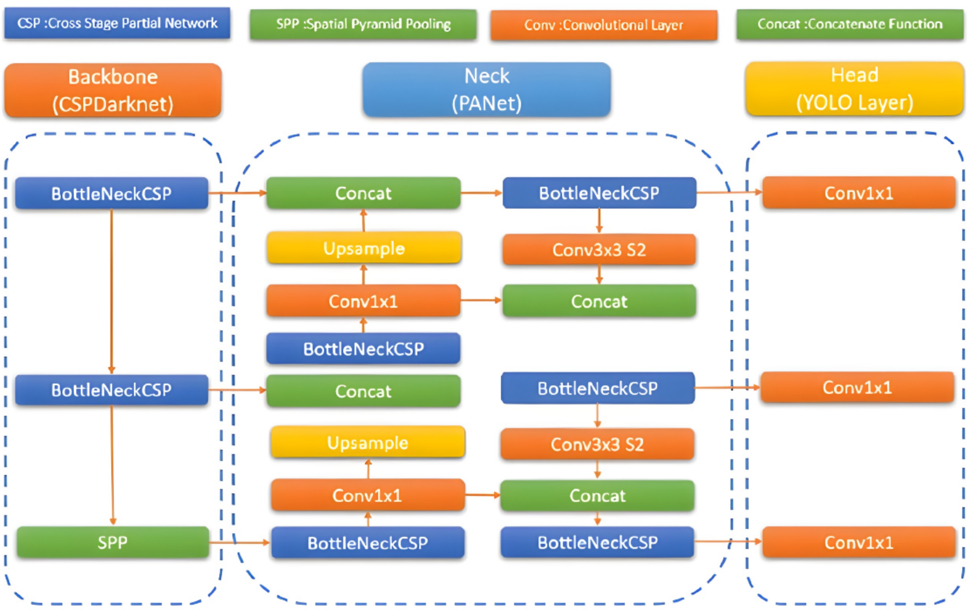

Fig. 3. YOLOv5 Architecture

2.1. Testing of test data

The testing phase included inputting several images of apple leaf diseases into the YOLOv5 architecture that have been developed. After obtaining the results, the next step was to evaluate the model's performance, which was carried out using the mean Average Precision (mAP). The expected outcome at this stage was to determine how accurately the model detected disease symptoms on apple leaves.

2.2. Model evaluation

The evaluation stage used the mAP as the primary measure. As shown in Fig. 4, the mAP value represented the average area under the precision-recall curve, which showed the operation of Intersection over Union (IoU). IoU measured the overlap between two boundaries, including the ground truth (correct reference) and the predicted output of the model. This metric was essential for assessing the performance of the model and the accuracy of its predictions in object detection tasks.

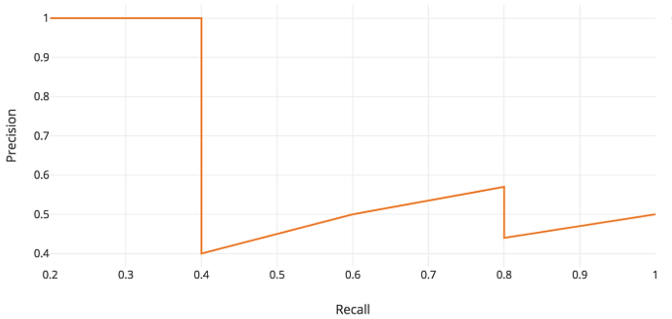

Fig. 4. Precision-Recall curve

2.3. Bullets

To assess classification model performance, four key outcomes, including true positive (TP), true negative (TN), false positive (FP), and false negative (FN), were analyzed. TP was an observation predicted to belong to the positive class, while TN was an observation predicted to belong to the negative class, which was correct. FP occurred when an observation was predicted to belong to the positive class, but it actually belonged to the negative class. FN occurred when an observation was predicted as negative, but it should have been classified as positive. The confusion matrix calculation incorporated these four combinations, as shown in Table 1.

Table 1. Confusion Matrix

Decision	Positive prediction	Negative prediction
Positive actual	TP	FN
Negative actual	FP	TN

The mAP calculation was derived in the operation of the Precision (p), Recall (r), AP, and IoU values in equations (1), (2), (3), and (4).

$$Precision = \frac{\text{TP}}{TP + FP} \tag{1}$$

$$Recall = \frac{\mathrm{TP}}{TP + FN} \tag{2}$$

$$AP = \int_0^1 p(r)dr \tag{3}$$

$$IoU = \frac{\text{Area of Overlap}}{Area\ of\ Union} \tag{4}$$

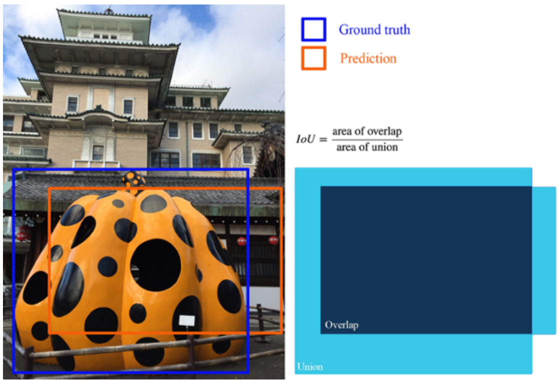

Fig. 5. Intersection over Union definition

The mAP calculation was based on the average of several IoU values, spanning an IoU range from 0.5 to 0.95 with a step size of 0.05, as shown in Fig. 5.

3. Results and Discussion

This research analyzed 120 data samples, each consisting of images depicting symptoms of four diseases affecting apple leaves, including Healthy, Scab, Black Rot, and Cedar Apple Rust. Each disease was represented in 30 images, all captured using a smartphone camera with an RGB resolution of 256 × 256 in JPG format. Similar methods have been used in related investigations, such as Xuan et al. [10], which adopted transfer learning to recognize red and green apples under varying lighting conditions and image sharpness to optimize the training process.

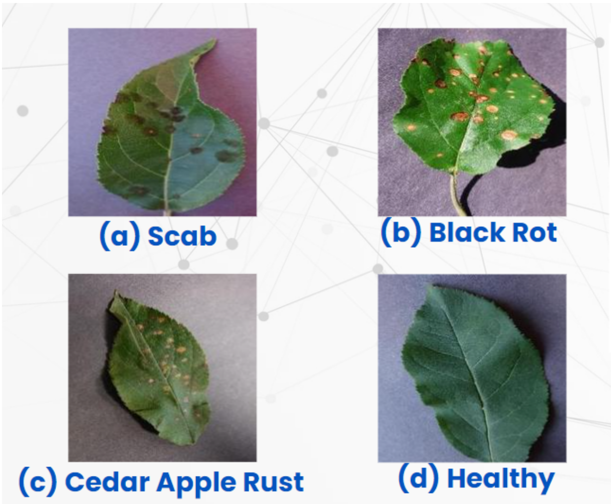

Fig. 6. Image of diseases on apple leaves

Each sample image was labeled to indicate the specific disease affecting the apple leaves. As presented in Fig. 6, the four distinct disease types on apple leaves were fully identified based on Petruzzello [32], showcasing characteristic symptoms such as green, purple, and brown spots of varying diameters, which was further explained in Table 2. Related research Ratnawati and Sulistyaningrum [8] used Random Forest algorithms to quantify disease severity on apple leaves, reporting that disease spots generally had a round shape with clear boundaries, gradually changing to a brownish-yellow center as the disease progressed. In cases of secondary infections, these spots might become irregular, with black spots (pycnidia clusters) often visible in the center. Unlike the previous investigation by Ratnawati and Sulistyaningrum [8], which focused on the presence of black spots to assess disease type, this research expanded on such results by identifying several disease indicators across multiple conditions on apple leaves.

Table 2. Diseases type

Label	Number	Pathogens	Symptoms
Scab	28	*Venturia inaequalis*	On both sides of the leaves, green spots appear that turn into purple-black as the disease progresses.
Black Rot	39	*Botryosphaeria obtusa*	Purple spots with a diameter of 0.2 to 0.125 inches appear on the leaf surface.
Cedar Apple Rust	42	*Gymnosporangium juniperi*-virginianae	Brown spots appear and make the leaves brittle.
Healthy	11	-	Dark green.

Based on Table 2, the majority of disease symptoms observed in apple leaf images appeared as brown spots, totaling approximately 42 instances, followed by purple and black spots. This pattern suggested that Cedar Apple Rust, caused by the fungus *Gymnosporangium juniperivirginianae*, was the predominant disease affecting the apple leaves. Following this initial analysis, the data proceeded to the annotation stage.

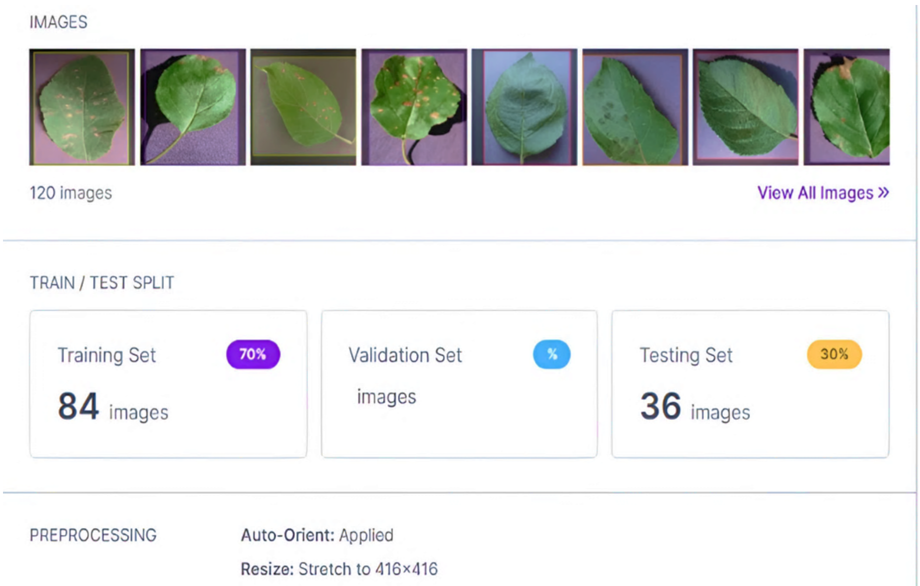

Fig. 7. Annotation results of apple leaf diseases

3.1. Data annotation

In the data annotation process, 120 images of apple leaves were labeled using bounding boxes to indicate specific symptoms of Scab, Black Rot, and Cedar Apple Rust. Annotation was carried out with Roboflow, as detailed in Fig. 6, enabling accurate identification of disease symptoms on apple leaves. It was similar to what Utami et al. [33] did for food nutrition annotation. The method worked well for looking at disease symptoms. Labels were put on each image for the symptoms found.

In Fig. 7, the annotation process through the use of bounding boxes successfully categorized the 120 disease images into eight groups. These images were split into two datasets, with 84 apple disease images allocated to training data and 36 images assigned to test data.

3.2. Data sharing

The data that was annotated got divided again into training and testing sets. These sets had images that were specific to symptoms of each disease. Specifically, 21 images were used for training, and nine images were designated for testing across each disease category. Table 3 presented the distribution of training and test data based on the symptoms observed.

Table 3. Distribution of Training and Test Data

Label	Training Data	Test Data
Healthy	21 (70%)	9 (30%)
Scab	21 (70%)	9 (30%)
Black Rot	21 (70%)	9 (30%)
Cedar Apple Rust	21 (70%)	9 (30%)

The data distribution was divided into 70% for training and 30% for testing, ensuring an appropriate balance for model accuracy. This allocation aimed to achieve a well-distributed dataset for optimal model performance. As shown in prior research on corn plant disease classification [21], a similar CNNs architecture with three convolutional layers, each with a 2x2 kernel size, was used. In the classification phase, an artificial neural network with two hidden layers was integrated into the model.

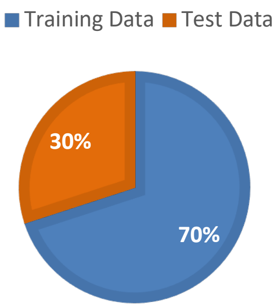

Fig. 8. Distribution of Training and Test Data

Fig. 8 showed the data distribution for each disease label, including Healthy, Scab, Black Rot, and Cedar Apple Rust, where blue sectors represented the training data (70%) and orange sectors represented the test data (30%). This clear segmentation ensured that each target label have a balanced and complete dataset without missing values.

3.3. Modeling YOLOv5 on CNN

YOLOv5 was constructed on CNNs, leveraging its high accuracy and rapid training capabilities. The model was subjected to eight repetitions of convolutional layers, culminating in a YOLO detection layer. The final YOLOv5 contained 7,071,633 parameters across 283 layers, as shown in Table 4. This setup was optimized for detecting and classifying disease symptoms with precision and efficiency.

Table 4. Development of the YOLOv5s model on CNN

Layer	*Output Shape*	*Param*
Conv	[63, 32, 3, 2]	18560
C3	[64, 64, 1]	18816
Conv	[128, 64, 3, 3]	73984
C3	[128, 128, 3]	156928
Focus	[32, 3, 3]	3520
Conv	[256, 128, 3, 2]	295424
C3	[256, 3, 256]	625152
Conv	[512, 256, 3, 2]	1180672
C3	[512, 512, 1, False]	1182720
SPP	[512, 512, [5, 9, 13]]	656896
Conv	[512, 256, 1, 1]	131584
Upsample	[None, 2, 'nearest']	0
Concat	[1]	0
Conv	[256, 128, 1, 1]	33024
C3	[512, 256, 1, False]	361984
Upsample	[None, 2, 'nearest']	0
Concat	[1]	0
Conv	[128, 128, 3, 2]	147712
C3	[256, 128, 1, False]	90880
Concat	[1]	0
C3	[128, 128, 3, 2]	296448
Conv	[256, 256, 3, 2]	590336
Concat	[1]	0
C3	[512, 512, 1, False]	1182720
YOLO Detect	[4, [[10, 13, 16, 30, 33, 23], [30, 61, 62, 45, 59, 119], [116, 90, 156, 198, 373, 326]], [128, 256, 512]]	24273

Table 4 provided details about the YOLOv5 architecture, which listed layers with different parameter counts. Some layers had many parameters, showing how the model could capture detailed features. However, other layers had no parameters and were only used to reshape tensors or combine data without adding complexity. The last YOLO Detect layer worked at three scales, making it seem complex and good at detecting objects.

The training process needed adjusting important hyperparameters like the learning rate, steps, momentum, weight decay, warmup epochs, and scaling factors. These were important for better model performance. Research by Utami et al. [33] stated YOLOv5 worked well and gave results like 98.6% accuracy, 0.95 precision, 0.96 recall, and an F1-Score of 0.95 when used for Indonesian food detection.

3.4. Testing test data

In the testing phase, the model was applied to both the training and test datasets, and subjected to 100 iterations or epochs to identify the best model configuration, as presented in Fig. 9.

Fig. 9. Testing Test Data

3.5. Evaluation model

Evaluating how the model worked was important for this research about classifying apple leaf disease symptoms. In Table 5, it showed numbers like Precision, Recall, mAP@0.5, and mAP@0.5:0.95. These numbers indicated how good the model was at finding diseases in apple leaves. The results showed the model was accurate at distinguishing the symptoms of diseases in apple leaves.

Table 5. Best Model

Class	Precision	Recall	mAP@ 0.5	mAP@ 0.5:0.95
All	0.810	0.981	0.950	0.765
Healthy	0.715	0.946	0.915	0.710
Scab	0.903	1.000	0.968	0.772
Black Rot	0.622	1.00	0.924	0.784
Cedar Apple Rust	1.000	0.980	0.995	0.792

The best model developed for detecting disease symptoms on apple leaves achieved a Precision of 0.810, Recall of 0.981, mAP@0.5 of 0.950, and mAP@0.5:0.95 of 0.765. These evaluation metrics indicated that the model was highly accurate and reliable for identifying apple leaf diseases.

4. Conclusions

In conclusion, this research showed the effectiveness of YOLOv5 for detecting apple leaf diseases, particularly Cedar Apple Rust, with a Precision of 0.810, Recall of 0.981, mAP@0.5 of 0.950, and mAP@0.5:0.95 of 0.765. The analysis indicated the importance of accurate disease detection for apple cultivation in sub-tropical regions, such as Indonesia. By enabling quick and precise identification, this model could support farmers in taking timely actions to enhance crop yield and quality. The ability of YOLOv5 to classify diseases such as Scab, Black Rot, and Cedar Apple Rust showed its potential to reduce crop losses due to disease. Despite certain limitations, including the limited sample size, the results offered a valuable basis for future research and suggested that a similar model could be applied in broader plant health management initiatives.

Abbreviations

YOLOv5	You Only Look Once version 5
CNNs	Convolutional Neural Networks
SCIS	Smart City Information System
PPO	Plant Pest Organisms
MLP	Multi-Layer Perceptron
mAP	mean Average Precision
IoU	Intersection over Union
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
p	Precision
r	Recall
RGB	Red Green Blue
JPG	Joint Photographic Group

Data availability statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request. The dataset used for this research consists of images of apple leaves affected by various diseases, which can be accessed through the following public repository: https://github.com/lzoran/plant-disease-dataset/tree/master/data. This dataset includes 120 images categorized into four groups: Healthy, Scab, Black Rot, and Cedar Apple Rust, with each category containing 30 images.

CRediT authorship contribution statement

Moh. Erkamim: Conceptualization, data collection, data analysis, initial draft writing, and revisions. Muhammad Zidni Subarkah: Methodology development, YOLOv5 modeling, results analysis, and writing the discussion section. R. Soelistijono: Research supervision, manuscript editing, and providing critical feedback on the content and structure of the article.

Declaration of Competing Interest

The authors of this manuscript declare no conflict of interest or competing interest.

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