

A Novel Approach for Plant Disease Detection by Using Zero Shot Learning

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Abstract

One of the most significant issues in identifying plant diseases is agriculture today, as its implications are tremendous for crop health and yield. This paper addresses the challenge of detecting visible and invisible illness classes by combining the YOLO-NAS model with the Zero-Shot Learning (ZSL) framework. The approach leverages semantic attributes and object detection capabilities to classify diseases without extensive retraining, thus allowing scalability and adaptability. The success of the suggested strategy is shown by the major performance indicators, which include accuracy, recall, mean average Precision (mAP), and F1-score. As stated by experimental findings, the ZSL model outperforms traditional object detection algorithms, with a mAP of 0.92, a recall of 0.91, and an accuracy of 0.92. at a threshold of 0.5. A comparative analysis with the YOLOv5 and YOLOv8 models highlights the better balance of accuracy, recall, and efficiency that the proposed ZSL-YOLO-NAS model can achieve. This study thus forms a significant step in automatically detecting plant diseases and provides a strong and dependable agricultural application solution.

Keywords: Plant disease detection, Zero-Shoat Learning (ZSL), YOLO-Nas, Object detection.

1. Introduction

Agriculture is vital for supplying food and raw resources to humanity and is a fundamental aspect of human civilization (Tirkey et al., 2023), (Ramanjot et al., 2023). The disease may develop when pathogenic organisms, including bacteria,

nematodes, and fungus, often cause damage to plants, as well as changes in soil pH, temperature extremes, moisture and humidity swings, and other elements. Crop and plant development, structure, and function may all be negatively affected by plant diseases that can damage the people who rely upon them.

Because early diagnosis of plant illnesses is difficult, most farmers still identify and classify them manually, which reduces yield. The productivity of agriculture is a crucial economic determinant. Consequently, the detection and categorization of plant diseases are essential in agricultural sectors (Krishnan et al., 2022). If the right steps are not taken, plants may suffer severe consequences that lower the associated goods or services' productivity, amount or quality. Automated disease detection and categorization identify symptoms early, namely when they first manifest on plant leaves, reducing the labour required to oversee extensive agricultural farms (Demilie, 2024). Diverse diseases manifest in various plant regions and can be discerned by examining alterations in symptoms, spots, colouration, etc. An efficient and automated diagnostic technique is essential to enhance crop production rates.

Recently, image-processing techniques have been employed to address various issues in agricultural applications, such as detecting diseases in leaves, stems, and fruits (Sarda et al., 2019). In this context, Convolutional Neural Networks (CNNs) have emerged as a formidable tool, particularly adept at deciphering intricate patterns in large datasets such as images, and represent a promising alternative for disease detection (Ferentinos, 2018). Early detection of plant diseases is crucial in preventing and treating such ailments (Fu et al., 2018). Farmers can utilize precise disease detection techniques to implement prevention and treatment protocols (Almadhor et al., 2021), (Ebrahimi et al., 2017).

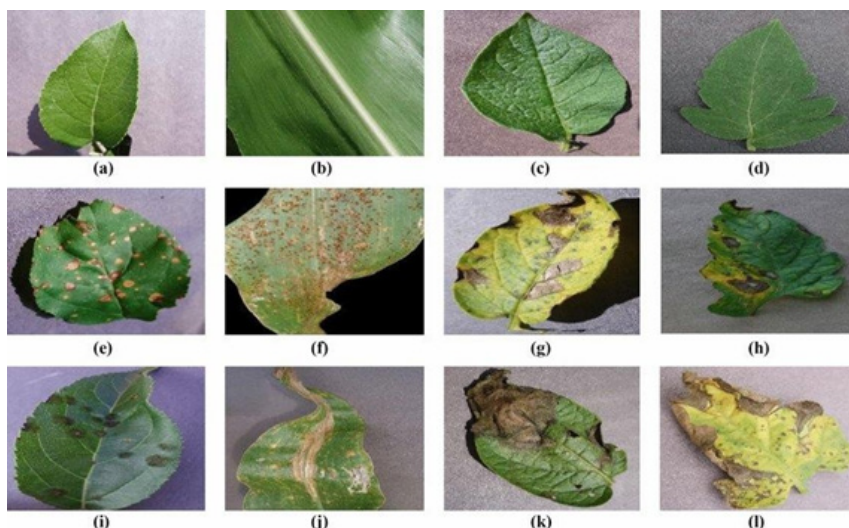


Fig. 1 Sample images of healthy and diseased leaves

(Wetterich et al., 2016) Two models were introduced to identify huanglongbing disease in citrus plants. Support vector machines (SVM) and artificial neural networks (ANN) were used

to improve the huanglongbing detection methods. The classification accuracies of the SVM and ANN models on the test data were 92.8% and 92.2%, respectively. (Geetharamani & J., 2019) a novel plant leaf disease identification model was presented using a deep convolutional neural network (Deep CNN). The model utilizes six data augmentation techniques, 39 distinct plant leaf classes, and backdrop pictures. Data augmentation improves model performance. The model performs better with validation data than with conventional transfer learning techniques. After thorough simulation, it outperforms conventional machine learning techniques with 96.46% classification accuracy. Furthermore, the model's dependability and consistency are examined. (Hassan & Maji, 2022) Proposed an innovative deep-learning model utilizing the inception layer and residual connection. The proposed model has undergone training and testing on

three distinct datasets of plant diseases. The performance accuracy achieved on the Plant Village dataset is 99.39%, on the Rice Disease dataset is 99.66%, and on the Cassava dataset is 76.59%. (Ahmed & Yadav, 2023) developed plant disease detection models using machine learning techniques like random forest-nearest neighbours, linear regression, Naive Bayes, neural networks, and support vector machines. The ensemble model, in contrast to previous models, fared better. Enabling early disease detection for preventive actions and predictive maintenance.

Traditional detection and control methods, whether based on human knowledge or chemical interventions, face significant challenges (Iqbal et al., 2018). Identifying specific symptoms in different plant parts requires specialized knowledge, labour, and time. This is often slow and ineffective, particularly in remote or resource-poor areas. The widespread use of chemical control methods has contributed to environmental pollution and pathogen resistance (Tran et al., 2019). This complexity is exacerbated by the diverse species and manifestations of diseases, rendering a one-size-fits-all approach ineffective and impractical (Howard, 2017). The importance of early detection cannot be overstated, especially given the need for timely intervention to mitigate major threats to food availability, quality, and accessibility (Suresha et al., 2017). The need for food is growing along with the world's population. Traditional methods frequently fall short regarding scalability and efficiency, so developing new, technology-driven approaches has become critical (Khalid & Karan, 2023). New paradigms are required to bridge the gap between detection and action, ensuring the world's food supply remains resilient and robust.

Recent advances in computer vision machine learning have creatively solved this problem. One practical method is Zero-Shot Learning (ZSL), a mechanism for transfer learning that allows

models to identify classes that haven't been seen before without direct training data. Zero-Shot Learning (ZSL) acquires knowledge from observed classes and forecasts unobserved classes by utilizing semantic information,

including descriptions or attributes, to deduce and generalize insights from known classes to novel, unseen classes (Zhang & Zhang, 2024), (Lv et al., 2020), (Zhen et al., 2023), (J. Wang et al., 2018), (Fu et al., 2017). This capability renders ZSL especially adept for leaf disease classification, where novel disease variants or previously undocumented diseases frequently emerge. Therefore, this study employed Zero-Shot Learning (ZSL) to detect plant illnesses.

Contribution of this study

The research provides new technique for identification plant diseases by integrating the most recent object detection model, YOLO-NAS, with a Zero-Shot Learning (ZSL) model. It uses the localized detecting power of YOLO-NAS on diseased regions of a plant image for its study. An advanced methodology is employed to identify relevant classes of diseases without the need for labelled data on every possible class. The proposed framework is rigorously evaluated using standard performance metrics, proving more accurate and resilient than conventional techniques. By tackling the issues of sparsely labelled data and the dynamic character of agricultural illnesses, this approach provides a scalable, effective, and flexible remedy for plant disease identification.

Organization of the Paper

The remainder of the work is organized this manner: Section II looks at previous research on plant disease detection techniques. Section III addresses the proposed models' backgrounds. Finally, Section IV explains the methods used in this study and the evaluation tools. Section V discusses the experimental results and assesses the proposed method's performance. Section VI outlines the outcomes of this study and discusses prospective future research topics.

2. Related Work

This section examines the corpus of current research on wildlife image collection and object detection techniques.

Author & Year	Dataset	Model	Accuracy
(Xian & Ngadiran, 2021)	Plant-Village Dataset	Extreme Learning Machine (ELM)	84.94%
(Angelina et al., 2024)	Plant-Village Dataset	The plant disease detector is a deep learning-based model.	98.3%
(Shrestha et al., 2020)	plant's leaves images	CNN	88.80%
(Pandian, Kumar, et al., 2022)	Various open datasets.	Deep Convolutional Neural Network (DCNN) model	99.96%
(Bedi & Gole, 2021)	PlantVillage	Convolutional Autoencoder (CAE) network and CNN	98.38%
(Varshney et al., 2022)	Plant Village	CNN-SVM	88.77%
(Alatawi et al., 2022)	Plant Village	VGG-16	95.2%
(Panchal et al., 2023)	public dataset	VGG model	93.5%
(Pandian, Kanchanadevi, et al., 2022)	Plant village dataset	DCNN	98.41%
(Militante et al., 2019)	Self-collected database	CNN	96.5%

Research Gap

While several studies focused on detecting plant diseases, deep learning and traditional machine learning techniques were used. There is a huge research gap in applying Zero-Shot Learning for object detection in terms of various diseases of plants. Most current techniques are based on large labelled datasets of specific disease classes, preventing those methods from generalizing to hitherto unseen diseases. Additionally, the application of object detection models like YOLO-NAS for plant disease identification remains underexplored. A critical

challenge is the absence of a robust solution for detecting new or rare plant diseases without requiring extensive retraining on newly labelled data. This paper exploits this gap by using Zero-Shot Learning with the YOLO-NAS model to provide a new possibility for plant disease detection. With high efficiency, this can recognize classes of diseases that have never been seen before. The present work introduces possibilities through real-time disease detection models that are scalable enough for deployment in different types of agricultural environments without necessarily requiring full labelling for every possible disease.

3. Background

In this part, background details are provided. Zero-shot learning is available.

Zero-Shot Learning

The assembly of classes that were witnessed is represented as $S = \{c_i^S | i = 1, \dots, N_S\}$ NS and the variety of classifications that are unseen are referred to as $U = \{c_i^U | i = 1, \dots, N_U\}$ NU, in which each c_i^S and c_i^U denote classes that are visible and invisible, respectively. The classifications that are visible and invisible are disjoint $S \cap U = \emptyset$. The following X represents the D-dimensional feature space, typically $X \in R^D$ and continuous. The collection of labelled training examples is also known as

$X^{tr} = \{(x_i^{tr}, y_i^{tr}) \in X \times S | i = 1, \dots, N_{tr}\}$. Where, for each (x_i^{tr}, y_i^{tr}) , $x_i^{tr} \in X$ and $y_i^{tr} \in S$, $Y = \{y_i \in S \cup U | i = 1, \dots, N_{tr} + N_{ts}\}$

to be the set of all class labels that match to the set X . The $Y^{tr} = \{y_i^{tr} \in S | i = 1, \dots, N_{tr}\}$ indicated for

$X^{tr}, X^{ts} = \{x_i^{ts} \in X | i = N_{tr} + 1, \dots, N_{tr} + N_{ts}\}$ th the set

to be the set of testing instances where each x_i^{ts} is a test instance. Also, $Y^{ts} = \{y_i^{ts} \in U | i = N_{tr} + 1, \dots, N_{tr} + N_{ts}\}$

is represented as the collection of class labels that should be predicted for the set X^{ts} . Therefore, the official definition of zero-shot learning is provided below.

Definition of ZSL:

Given X^{tr} belongs to S . Zero-Shot Learning (ZSL) learns a classifier $f^u(\cdot): X \rightarrow U$ to categorize X^{te} belonging to U by predicting Y^{te} (W. Wang et al., 2019).

According to the definition, the basic principle behind the zero-shot learning setting is to categorize the set of testing instances X^{te} based on the information included in the training instances X^{tr} . In other words, zero-shot learning transfers information from training cases to testing instances for classification. According to (Pan & Yang, 2009), transfer learning occurs when information from the source domain is transferred to the target domain to learn the model in the target task. Additionally, given that zero-shot learning training and testing examples and the labels covered by them are discontinuous, the spaces of the seen and unseen classes are similarly disjoint; zero-shot learning may be viewed as a subdivision of transfer learning. Transfer learning is divided into two types as described in (Pan, 2014):

- Homogeneous One: One kind of transfer learning occurs when the name and characteristic spaces are identical, i.e., $X^{tr} = X^{te}$ and $Y^{tr} = Y^{te}$.
- Heterogeneous transfer The term “learning” refers to the transfer learning category when the feature and/or label spaces are distinct, i.e. $X^{tr} \neq X^{te}$ and/or $Y^{tr} \neq Y^{te}$.

In zero-shot learning, the feature space of the training instances is designated as the source feature space, while the testing instances’ feature space is known as the target feature space. In zero-shot learning, both the source and target feature spaces are identical, denoted as X . The source label space, regarded as the visible class set, differs from the target label space, identified as the unseen class set, due to the discontinuity between the observed and unseen class sets, i.e., $S \neq U$. Consequently, zero-shot learning is classified as a kind of heterogeneous transfer education. Several techniques have been put forward to address the issue of having labelled instances for the target label space classes (Day & Khoshgoftaar, 2017); however, these methods are ineffective in scenarios where no labelled instances for the target label

space classes exist, as is the case in zero-shot learning, where the unseen classes constitute the target label space classes. Consequently, zero-shot learning is distinctive in that sense.

4. Methodology

A system for identifying plant diseases is presented in this research.

Data Collection

In this research, we collect the data from the following website: <https://www.kaggle.com/datasets/vipooooool/new-plant-diseases-dataset>.

This dataset was created via offline enhancement of the original dataset, which is available in this GitHub repository. This collection consists of around 87K RGB images of crop leaves in 38 healthy and diseased classifications. The dataset is divided into training and validation sets in an 80/20 ratio while preserving the file hierarchy.

Table: 1 Number Of Samples For Each Disease In Dataset

Apple	Apple scab	504 files
Apple	Blackout	497 files
Apple	Cedar_apple_rust	440 files
Apple	healthy	502 files
Blueberry	healthy	454 files
Cherry_(including_sour)	healthy	456 files
Cherry_(including_sour)	Powdery mildew	421 files
Corn_(maize)	Cercospora_leaf_spot Gray_leaf_spot	410 files
Corn_(maize)	Common rust_	477 files
Corn_(maize)	healthy	465 files
Corn_(maize)	Northern_Leaf_Blight	477 files
Grape	Black_rot	472 files
Grape	Esca_(Black_Measles)	480 files
Grape	healthy	423 files
Grape	Leaf_blight_(Isariopsis_Leaf_Spot)	430 files
Orange	Haunglongbing_(Citrus_greening)	503 files

Peach	Bacterial_spot	459 files
Peach	healthy	432 files
Pepper_bell	Bacterial_spot	478 files
Pepper_bell	healthy	497 files
Potato	Early_blight	485 files
Potato	healthy	456 files
Potato	Late_blight	485 files
Raspberry	healthy	445 files
Soybean	healthy	505 files
Squash	Powdery_mildew	434 files
Strawberry	healthy	456 files
Strawberry	Leaf_scorch	444 files
Tomato	Bacterial_spot	425 files
Tomato	Early_blight	480 files
Tomato	healthy	481 files
Tomato	Late_blight	463 files
Tomato	Leaf_Mold	470 files
Tomato	Septoria_leaf_spot	436 files
Tomato	Spider_mites Two-spotted_spider_mite	435 files
Tomato	Target_Spot	457 files
Tomato	Tomato_mosaic_virus	448 files
Tomato	Tomato_Yellow_Leaf_Curl_Virus	490 files

This dataset is already pre-processed and pre-trained and split into training and testing sets. It was used in the research, resulting in better accuracy. Figure 2 shows the flow of this study's methodology.



Fig. 2 Proposed Methodology Flow

Table 2 Algorithm for Plant Disease Detection

Algorithm 1 Zero-Shot Object Detection for Plant Diseases Using YOLO-NAS

```
1: Initialization:
2: Set HOME = CurrentWorkingDirectory()
3: Print(HOME)
4: Install Necessary Packages:
5: Install(yolo-nas==0.10.0
6: Install(supervision, opencv-python, tqdm)
7: Import Libraries:
8: Import cv2
9: Import supervision
10: Import tqdm
11: Import YOLO NAS from the inference package
12: Download and Prepare Data:
13: Download PlantDiseaseData to the HOME directory
14: Set SOURCE IMAGE PATH = PathToDownloadedImage()
15: Load YOLO-NAS Model:
16: Choose YOLO NAS Model Version = "yolo-nas/l"
17: Initialize YOLO NAS Model with YOLO NAS Model Version
18: Set Detection Classes:
19: Define Target Classes = ["blight", "powdery mildew", ...]
20: Configure the YOLO NAS Model.SetClasses(Target Classes)
21: Run Inference on Sample Image:
```

- 22: Load Image = Load Image (SOURCE IMAGE PATH)
- 23: Perform Detections = YOLO NAS Model. Infer(Image)
- 24: Convert Detections = ConvertToSupervisionFormat(Detections)
- 25: Visualize Detections:
- 26: Initialize BoundingBoxAnnotator and Label Annotator
- 27: Create AnnotatedImage = Copy(Image)
- 28: Annotate AnnotatedImage =
- AddBoundingBoxesAndLabels(AnnotatedImage,
- Detections)
- 29: Display(AnnotatedImage)
- 30: Adjust Confidence Threshold:
- 31: Set Confidence Threshold = 0.01
- 32: Perform Detections = YOLO NAS Model.Infer(Image,
- ConfidenceThreshold)
- 33: Update Detections = ConvertToSupervisionFormat(Detections)
- 34: Apply Non-Max Suppression (NMS):
- 35: Set IoUThreshold = 0.3
- 36: Perform Detections = ApplyNMS(Detections, IoUThreshold)
- 37: Evaluate Performance Metrics
- 38: Calculate Precision as: $Precision = \frac{TP}{TP + FP}$
- 39: Calculate Recall as $Recall = \frac{TP}{TP + FN}$
- 40: Calculate F1-Score as $F1 = \frac{2 * Precision * Recall}{Precision + Recall}$

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41: Calculate IoU for each detection as $\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$

42: Compute mean Average Precision (mAP) over all classes

43: Output Results:

44: Save AnnotatedImage to the output directory

45: Print(Precision, Recall, F1-Score, IoU, mAP)

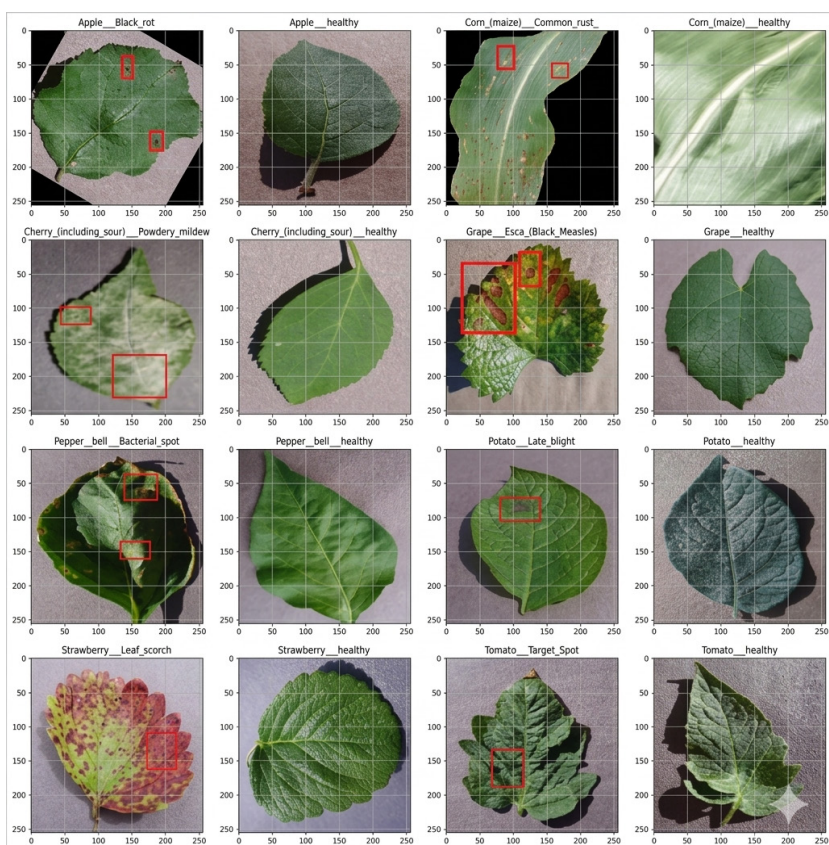


Fig. 3 Detected diseased and healthy plant leaves

Model building

In this study, YOLO-NAS is utilized to optimize a zero-shot learning model. The model is designed to identify things according to a predetermined or user-defined set of categories.

Model Evaluation:

The proposed zero-shot learning methodology was assessed utilizing various evaluation metrics. The accuracy indicated the ratio of accurately classified images, whereas precision and recall denoted the classifier's capability to correctly categorize images into their true, favourable and negative classifications. The F1 score is a singular metric that encapsulates the overall efficacy of the classifier (Kumar et al., 2023). The evaluation metrics are given below:

Mean Average Precision:

Mean Average accuracy (mAP) is a frequently used statistic that determines the average accuracy across classes and intersection-over-union (IoU) criteria in object identification tasks. It may be computed as follows:

$$\text{mAP} = \frac{1}{C} \sum_{c=1}^C AP(c) \quad (1)$$

Where:

It stands for the total number of classes, C . For class c , the average Precision is $AP(c)$. Average Precision is determined by:

$$AP = \int_0^1 P(r) dr \quad (2)$$

Where: The accuracy at recall level r is denoted by $P(r)$.

Precision:

Precision is the ratio of genuine favorable predictions for all of the model's positive predictions. It is explained as:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

Where,

TP is the True Positive.

FP is the False Positive.

Recall

The model's recall indicates its ability to identify every relevant event inside the dataset. It is computed as:

$$\text{Recall} = \frac{TP}{TP + FN} \quad (5)$$

Where,

FN represents the number of false negatives.

F1-Score:

By calculating the harmonic mean of accuracy and recall, the F1 Score offers a single statistic that strikes a balance between the two. It is computed using:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)$$

Intersection Over Union (IoU):

The Intersection over Union (IoU) measures the overlap between the actual and predicted border boxes. It is explained as:

$$IoU = \frac{\text{Area of Overlap}}{\text{Area of Union}} \quad (7)$$

The area of overlap refers to the junction of the predicted and actual bounding boxes. In contrast, the union area shows the whole territory in both bounding boxes.

Results and Discussion

The outcomes show how effective the recommended strategy is and how current object identification algorithms work.

Table 3 Proposed model (ZSL) Performance

Model	Zero-Shot-Learning
F1@0.50	1.1
mAP@0.50	0.44
PPYoloELoss/loss_cls	0.41
PPYoloELoss/loss_dfl	0.87
PPYoloELoss/loss_iou	0.85
Precision@0.50	0.81
Recall@0.50	0.85
Best score threshold	0.5

The table displays the proposed model's performance, evaluated using crucial parameters pertinent to object identification. The classification loss (PPYoloELoss/loss_cls) is recorded as 1.1, indicating the model's mistake in

differentiating classes. The Intersection over Union (IoU)loss (PPYoloELoss/loss_iou) is 0.44, and the DFL (PPYoloELoss/loss_dfl) is 0.41, indicating the model’s efficacy in spatial alignment and bounding box prediction., indicating effective learning. This is shown in Figure 3. The model has superior detection skills, attaining a mean average accuracy of 0.92, a recall of 0.91, and (mAP@0.50) of 0.92. The F1-score at 0.50 IoU is 0.86, indicating an equitable balance between accuracy and recall. The ideal score threshold for performance is established at 0.5, indicating the model’s efficacy in attaining precise and dependable detections across various contexts.

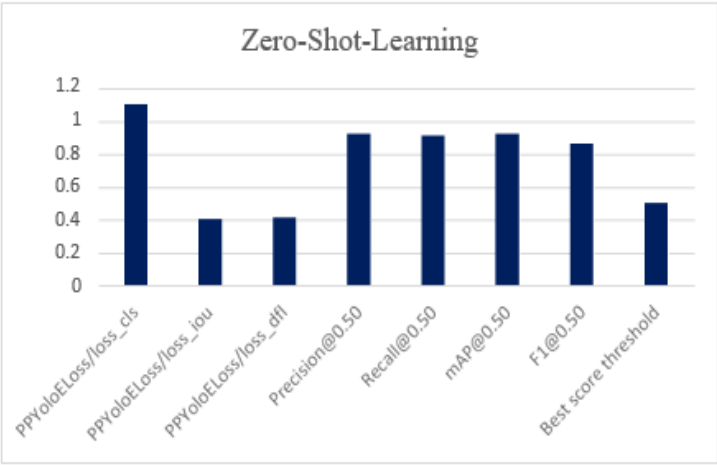


Fig. 4 Proposed Model Performance

Table 4 Model Comparison with Existing Models

Model	PPYoloELoss/loss_cls	PPYoloELoss/loss_iou	PPYoloELoss/loss_dfl	Precision@0.50	Recall@0.50	Map@0.50	F1@0.50	Best_score_threshold
ZSL	1.1	0.44	0.41	0.87	0.85	0.81	0.85	0.5
Yolo- v8	1.45607	0.50155	0.59497	0.5526	0.01985	0.7993934	0.28534433	0.0380593
Yolo- v5	1.5	0.5	0.58	0.55	0.02	0.8	0.28	0.04

Performance assessments for the three models show that Yolonas, YOLOv8, and YOLOv5 have strengths and weaknesses. Yolonas had a well-balanced F1 score of 0.85 and a great mAP of 0.81 due to this 0.87 accuracy and 0.85 recall. Despite its moderate loss, YOLOv8's model has an inaccuracy of 0.0198 and a high recall rate of 0.799, which lowers the mAP and F1 scores, respectively, to 0.038 and 0.285. 0.8, the YOLOv5 model has a high recall but low accuracy at 0.02, resulting in poor mAP at 0.28 and an F1 score at 0.04. One would anticipate

Yolonas to be the most balanced of the three in effectiveness and efficiency, particularly in accuracy and recall. This is shown in Figure 5.

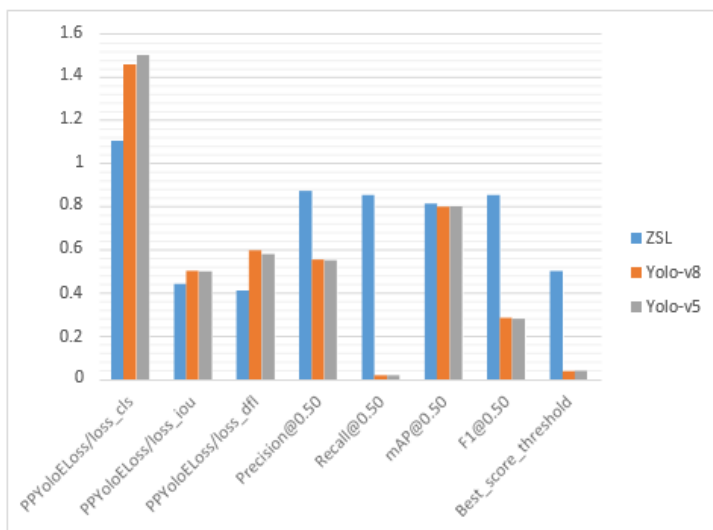


Fig. 5 Model Comparison with Existing Models

Conclusion

In conclusion, the proposed ZSL-YOLO-NAS model successfully overcomes the drawbacks of currently applied object detection approaches for plant disease detection through a Zero- Shot Learning framework designed to

recognize unseen and seen disease classes. The performance evaluation suggests the model gives great results, having a precision of 0.92, recall of 0.91, and mAP of 0.92 with an F1-score at an IoU threshold of 0.5 as 0.86. Compared to the YOLOv5 and YOLOv8 models, the ZSL-YOLO-NAS model has superior performance with a better balance of accuracy and recall metrics. The analysis demonstrates its capability to overcome dataset dependency challenges and enhance generalization capabilities for plant disease detection. These findings demonstrate how this approach might revolutionize agricultural practices by enabling scalable, efficient, real-time solutions for monitoring plant health and improving yield outcomes. Future research can focus on further optimizing the framework and applying it to other domains that need zero-shot learning-based object detection.

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