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Comparative Evaluation of Inception V3 and YOLOv8 for Strawberry Plant Diseases Classification Using Deep Learning Models

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Abstract

Plant diseases and pests threaten agricultural productivity, with leaf diseases causing major crop losses. Early detection is essential to mitigate these impacts. This study presents a system for detecting strawberry leaf diseases using deep learning-based Convolutional Neural Networks (CNNs) by utilizing two pre-trained models, Inception V3 and YOLOv8, to classify leaves as healthy or diseased. A custom dataset of 5,192 images, comprising one healthy class and four disease-infected categories (leaf blight, blotch, scorch, and spot), is used. Inception V3 achieved 93.8% accuracy, while YOLOv8 outperformed it with 95.4% accuracy, a mAP of 78.6%, and precision, recall, and F1-scores of 89%, 88%, and 89%, respectively. With a compact size of 12 MB and a rapid inference time of 10 ms per image, YOLOv8 is highly suitable for real-time applications. These findings highlight YOLOv8's potential to improve agricultural productivity and food security through precise and efficient disease detection.

A. Introduction

Strawberry plants are vulnerable to various diseases that can severely affect yield and quality, making early detection and effective management essential for farmers. Traditionally, plant disease identification relied on visual inspection, a time-consuming and labour-intensive process prone to errors, particularly in large fields. With the rapid advancement of artificial intelligence (AI) and deep learning, especially Convolutional Neural Networks (CNNs), there has been a shift toward automated plant disease detection. Models like Inception V3 and YOLOv8 have shown great potential in image classification and object detection tasks.

The performance of Inception V3 and YOLOv8 is evaluated for detecting diseases in strawberry plants, focusing on key metrics such as accuracy, precision, recall, F1-score, and real-time capability. This study aims to provide valuable insights for farmers, researchers, and developers, facilitating the selection of the most suitable AI model for integrating plant disease detection into agricultural practices.

Traditional diagnostic methods, which rely on expert visual inspection, are time-consuming and require specialized knowledge. To overcome these limitations, researchers have adopted computer vision and deep learning techniques, which greatly improve both the efficiency and accuracy of disease detection.

Inception V3 excels in identifying patterns within complex datasets and is known for its robust classification capabilities, making it ideal for disease detection [1]. YOLOv8, part of the well-known You Only Look Once (YOLO) family, is optimized for real-time object detection and localization, making it particularly suitable for dynamic environments like field-based plant disease monitoring [2].

Convolutional Neural Networks (CNNs) have demonstrated remarkable success in image classification tasks, including plant disease detection. Popular models such as AlexNet, GoogLeNet, VGG, Inception V3, ResNet, and Xception achieve high classification accuracy. However, deeper networks often face challenges like the vanishing gradient problem, which can be addressed using residual modules. Particularly, Inception V3 has been widely applied in agricultural diagnostics, while models like YOLO and other deep learning architectures have also been explored for plant disease classification, improving both speed and accuracy.

Xiao et al. [3] proposed a model utilizing the ResNet-50 architecture to detect various strawberry diseases, including leaf blight, gray mold, and powdery mildew. The model achieved its highest training accuracy after 20 epochs, reaching 98.06% on the original dataset and 99.60% on the feature-enhanced dataset.

Pramudhita et al. [4] developed an automatic model for identifying strawberry leaf diseases, including powdery mildew, spider mites, and caterpillar infestations, using MobileNetV3-Large and EfficientNet-B0 architectures. The best performance was achieved with MobileNetV3-Large, reaching 92.14% accuracy with the RMSProp optimizer, a learning rate of 0.0001, and 70 epochs.

Quy Thanh Lu [5] utilized of renowned Convolutional Neural Network (CNN) models, including EfficientNetB5, MobileNet, ResNet50, InceptionV3, and VGG16, for plant disease classification. The study also compared the results with some deep learning models and with state-of-the-art. Among the tested CNNs, EfficientNetB5 demonstrated the best performance, achieving an impressive 99.2% classification accuracy, outperforming other models.

Gehlawat et al. [6] conducted a comparative study involving Xception, Inception V3, and Inception-ResNet v2 to detect fungal diseases in fruit plants. The Xception model achieved the highest accuracy (98.98% training, 99.34% testing) with strong learning capabilities and low training loss. Inception V3 showed good performance with high recall and precision, but lower accuracy. Inception-ResNet v2, while efficient, lagged in accuracy but may still be useful in resource-constrained scenarios.

On the other hand, the You Only Look Once (YOLO) model, renowned for its real-time object detection capabilities, has gained significant attention for its potential in dynamic agricultural environments. Its latest version, YOLOv8, is specifically designed for high-speed performance, allowing it to detect and localize objects in real time.

Jhatial et al. [7] developed a deep learning model using YOLOv5 to detect rice leaf diseases early and improve crop productivity. The dataset, comprising 400 diseased leaf images from the Kaggle website, was used to train, validate, and test the model on the Google Colab platform. The YOLOv5 model, upgraded from earlier YOLO versions, demonstrated superior accuracy, achieving precision, recall, and mAP values of 1.00, 0.94, and 0.62, respectively, after 100 training epochs.

Zayani et al. [8] incorporated a deep learning approach based on the YOLOv8 algorithm for automated tomato disease detection. By augmenting an existing Roboflow dataset, the model achieved an overall accuracy of 66.67%. However, class-specific performance varied, underscoring challenges in distinguishing certain diseases.

Alshammari et al. [9] employed YOLOv8 to detect *Tuta absoluta* infestations on tomato leaves, reporting 97% accuracy for healthy leaves and 85% accuracy for infected ones. The findings showcased deep learning's potential in precision agriculture for real-time pest monitoring and automated crop health management.

According to the information provided, both Inception V3 and YOLOv8 have shown effectiveness in plant disease detection, although each model has strengths and limitations. Inception V3 offers high accuracy but is less suitable for real-time use due to its computational demands, whereas YOLOv8 enables real-time disease detection but compromises some accuracy. This study compares both models to identify the one best suited for practical strawberry plant diseases classification.

B. Methodology

This section examines the theoretical principles, methodologies, and applications of CNN, Inception V3, and YOLOv8 for accurate strawberry plant disease diagnosis in agriculture.

1. CNN Architecture

A Convolutional Neural Network (CNN) is a multi-layer feed-forward neural network and one of the most popular deep learning models. CNNs operate through a series of layers, where the number of features extracted increases as the network depth grows. The architecture of a CNN is composed of several key layers: input, convolution, pooling, fully connected, and output layers. The input layer receives the image data provided to the network. Convolution layers apply filters across the image to extract essential features by identifying specific patterns [10]. The convolution result is processed through an activation function, such as ReLU, softmax, sigmoid, or tanh, to determine the output value [11]. Pooling layers help reduce the dimensionality of the feature maps by summarizing subregions of the image into a single representative value, such as the maximum or average. Fully connected layers interpret these features and perform classification tasks [12], as illustrated in Figure 1.

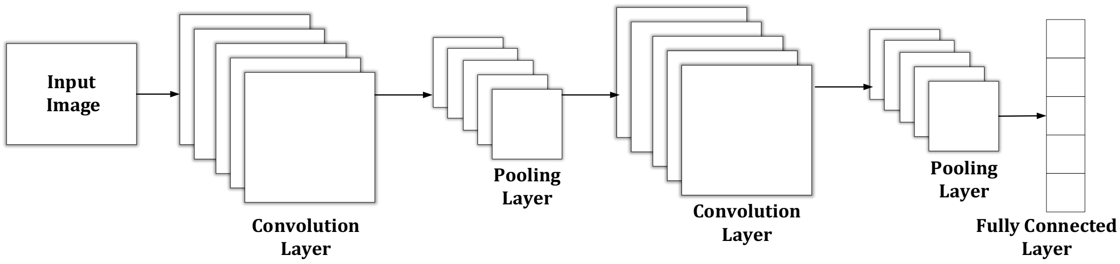


Figure 1. The Working Flow of the CNN Model

In mathematical notation, the input image is represented by S, and the kernel (filter) is denoted by F. The coordinates of the output feature map are indicated by i and j, while m and n refer to the row and column indices of the resulting matrix, respectively, as shown in Equation (1). The convolution operation [12] is defined as:

$$(S * F)(i, j) = \sum_m \sum_n S(m,n)F(i-m, j-n). \quad (1)$$

2. Inception V3 Model

Inception V3 [13] is a deep learning architecture developed by Google for image classification. Part of the Inception family, it is known for its innovative use of convolutional layers with varying filter sizes to capture textures and patterns at different scales. The model employs Inception modules, combining convolutional layers of various filter sizes (1x1, 3x3, 5x5) with pooling layers to enhance feature extraction and performance. It processes information across different abstraction levels, supported by auxiliary classifiers for improved learning in deeper layers. Figure 2 illustrates the network training process of the Inception V3 module.

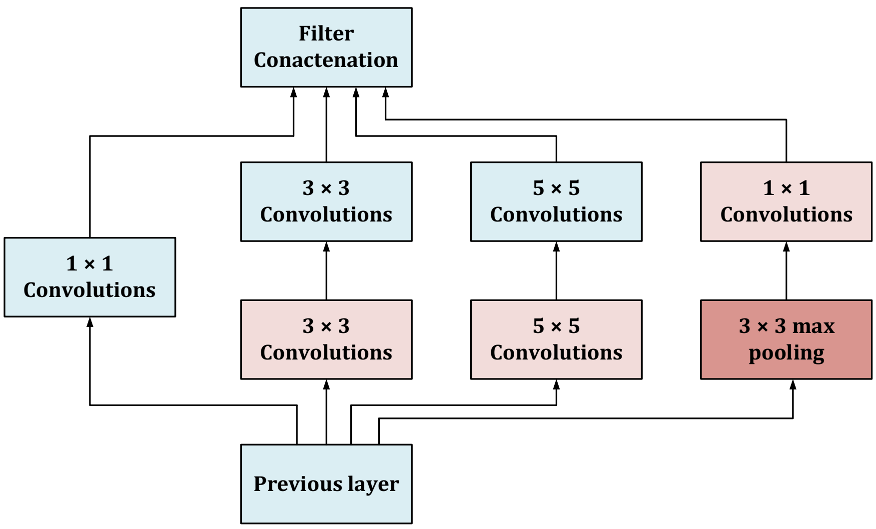


Figure 2. Block Diagram of the Inception V3 Module [14]

3. YOLOv8 Model

YOLOv8 (You Only Look Once version 8) is the latest version of the YOLO series, designed for real-time object detection. Its architecture consists of 53 convolutional layers, allowing it to perform both localization and classification in a single forward pass [15]. Available in versions from YOLOv8n (lightest) to YOLOv8x (heaviest), YOLOv8n is used in this research for its balance of accuracy, speed, and lightweight design [16]. Its architecture, as illustrated in Figure 3, comprises three components: Backbone, Neck, and Head. The Backbone integrates C2f and SPPF modules for lightweight efficiency and gradient flow, while the Neck retains critical feature information with up-sampling convolutional structures [17]. The Head uses an anchor-free, decoupled design for faster convergence, producing bounding box coordinates, confidence scores, and class labels [18].

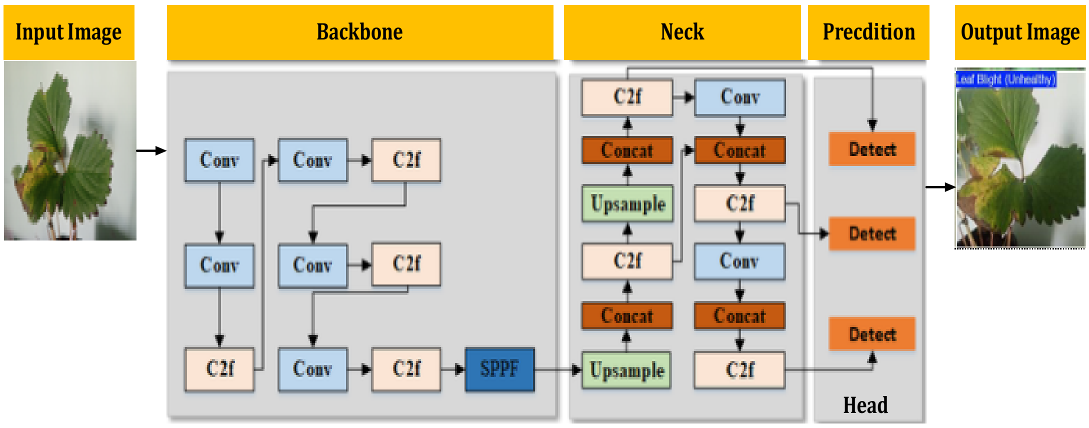


Figure 3. YOLOv8 Architecture Diagram

C. System Architecture Overview

Next, we train the models using the Inception V3 and YOLOv8 architectures and compare their performance based on the evaluation results. Figure 4 illustrates the proposed approach for classifying strawberry plant diseases.

1. Image Collection

The image dataset, consisting of infected and healthy plant images, was initially collected directly from plants using a Z05 720P HD Webcam (640 × 480 resolution) under bright daylight conditions and then loaded for processing. The dataset used in the study comprised a total of 5,192 images of strawberry plant leaves, categorized into five classes: healthy leaf (1,122 images), leaf blight (1,143 images), leaf blotch (1,122 images), leaf scorch (1,163 images), and leaf spot (642 images).

2. Dataset Splitting

The study used a diverse dataset of strawberry plant leaves, containing images of both healthy leaves and leaves infected with diseases like blight, blotch, scorch, and spot. The dataset was divided into three distinct subsets for training, validation, and testing purposes. Out of a total of 5,192 images, 3,634 images (70%) were allocated to the training set, 1,040 images (20%) to the validation set, and 518 images (10%) to the testing set.

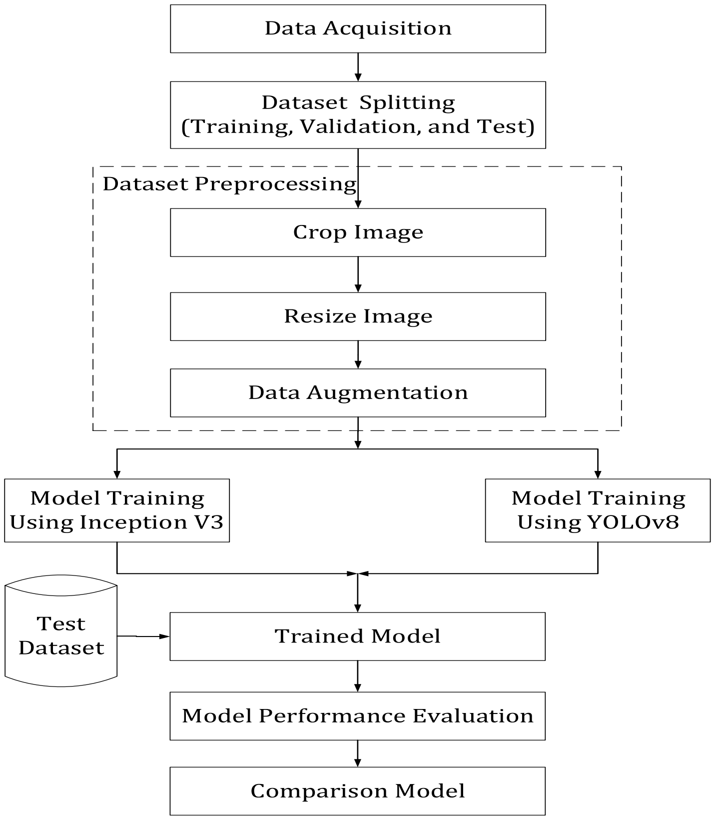


Figure 4. Proposed Approach For Strawberry Plant Diseases Classification

3. Data Augmentation

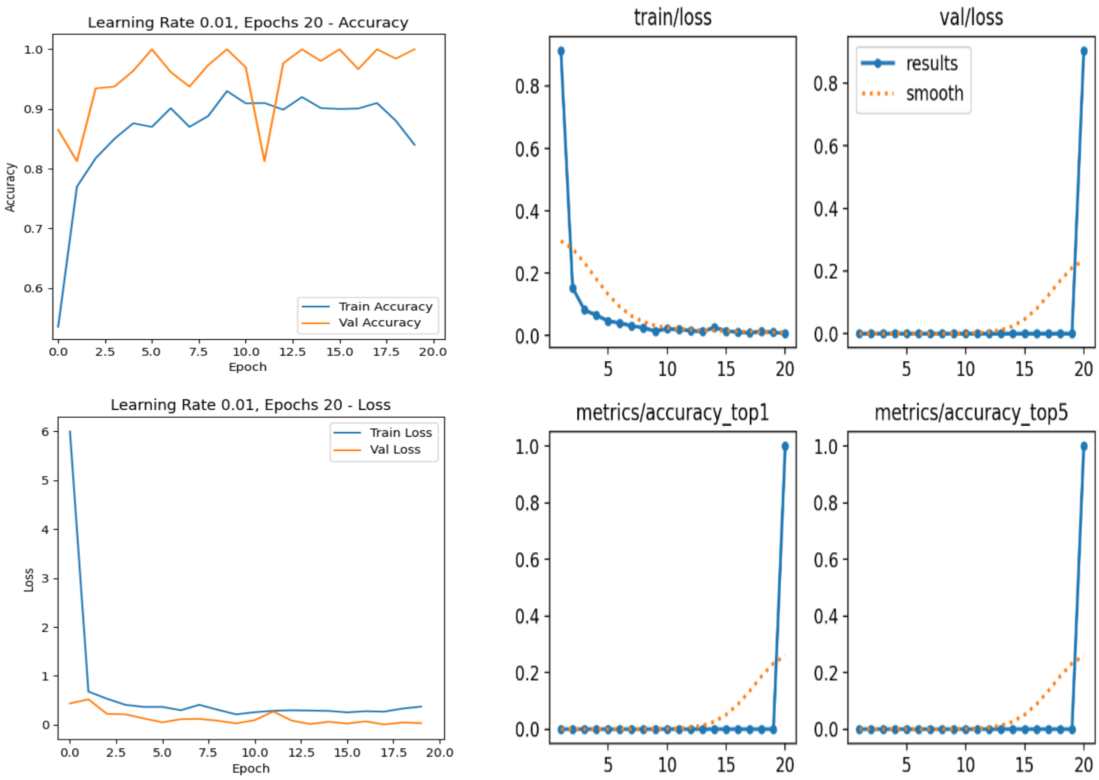
Inception V3 used basic geometric augmentations, such as cropping, brightness adjustment, and shifting, while YOLOv8 employed a broader range of augmentations, including flipping, translation, mosaic, and color adjustments, with flexible parameters configured in the "args.yaml" file. YOLOv8 also applied dynamic augmentation, transforming the dataset during each epoch to enhance sample variety and improve model performance. The details of the augmentation hyperparameters are summarized in Table 1.

Table 1. Table of Augmentation Hyperparameters

No.	Name	Function
1	hsv_h	0.015
2	hsv_s	0.7
3	hsv_v	0.4
4	translate	0.1
5	scale	0.5
6	fliplr	0.5
7	mosaic	1.0
8	erasing	0.4
9	crop_fraction	1.0

4. Models' Training and Hyperparameter Fine Tuning

In this step, a model is developed to detect infected strawberry leaves using Inception V3 for classification and YOLOv8 for detection and localization, both trained on the pre-processed dataset with optimized parameters. The hyperparameters used for training all models are as follows: the AdamW optimizer, a learning rate of 0.01, 20 epochs, an image size of 224, and a batch size of 16. The loss functions include box, classification (cls), distribution focal loss (dfl), pose, and keypoint objectness (kobj). Figure 5 illustrates the training and validation losses of both models over 20 epochs.



(a) (b)

Figure 5. Results of Training And Validation Losses (a) Inception V3 Model, and (b) YOLOv8n Model

Figure 5(a) shows that the model exhibits effective learning, with training accuracy rapidly approaching nearly 100% within the first 5 epochs and stabilizing thereafter. Validation accuracy follows a similar trend, indicating strong generalization to unseen data and minimal risk of overfitting. Training loss decreases sharply during the initial epochs and approaches zero by epoch 10, while validation loss stabilizes at a low value, further confirming the model's robustness and balanced performance without signs of overfitting or underfitting.

Figure 5(b) indicates that the model demonstrates effective learning, with steadily decreasing training and validation losses, reflecting good generalization and the absence of overfitting. The top-1 and top-5 accuracy metrics highlight its strong classification performance and robust predictions. Additionally, the smoothed trends further confirm the model's reliability across all metrics.

5. Prediction Results

A collection of strawberry leaf images, including both diseased leaves with symptoms and healthy samples, is shown in Figure 6. These images form the training dataset used to develop a deep learning model for classifying plant leaf diseases, with the proposed models applied for training.

- **Strawberry Leaf (Healthy):** These images show healthy, green strawberry leaves without visible disease symptoms.
- **Leaf Blotch (Unhealthy):** Leaf blotch, caused by *Gnomonia comari*, starts as brown, circular spots with purple borders that expand into large, light brown necrotic areas. It is characterized by brown or black spots on the leaves, indicating fungal or bacterial infection.
- **Leaf Blight (Unhealthy):** Leaf blight, caused by *Dendrophoma obscurans*, appears after harvest with enlarging round to elliptical spots (1/4 to 1 inch in diameter). It causes discolored, withering, and decaying areas on the leaf edges and surfaces, distinguishing it from leaf spot and leaf scorch.
- **Leaf Scorch (Unhealthy):** Leaf scorch, caused by *Diplocarpon earliana*, affects strawberry plants at any leaf development stage. It is marked by round to angular dark-purple spots that enlarge and resemble tar drops due to black fungal fruiting bodies. The condition also causes browning or drying of leaf margins, often due to environmental stress or infections.
- **Leaf Spot (Unhealthy):** Leaf spot, caused by *Mycosphaerella fragariae*, affects leaves, petioles, runners, and fruit stalks. The disease manifests as small, round purple spots that turn tan or gray with dark margins, mainly affecting young, succulent plant parts, with similar symptoms on most tissues except the fruit [19].

(a) (b) (c) (d) (e)

Figure 6. Sample Dataset Image of Strawberry Plant Leaves (a) Healthy Leaf, (b) Leaf Blotch, (c) Leaf Blight, (d) Leaf Scorch, and (e) Leaf Spot

A dataset of leaf images with disease regions annotated in YOLOv8 format, including bounding box details for various diseases, is illustrated in Figure 7. This figure demonstrates the diversity of the dataset used to train a model, showing both healthy and diseased leaf samples with augmentations applied to improve model performance.

A portion of the validation dataset, featuring strawberry leaf images labeled as healthy or unhealthy, is presented in Figure 8. The images highlight the clarity and reliability of the dataset, showcasing a range of disease conditions and healthy leaves to assess the model's predictive accuracy.

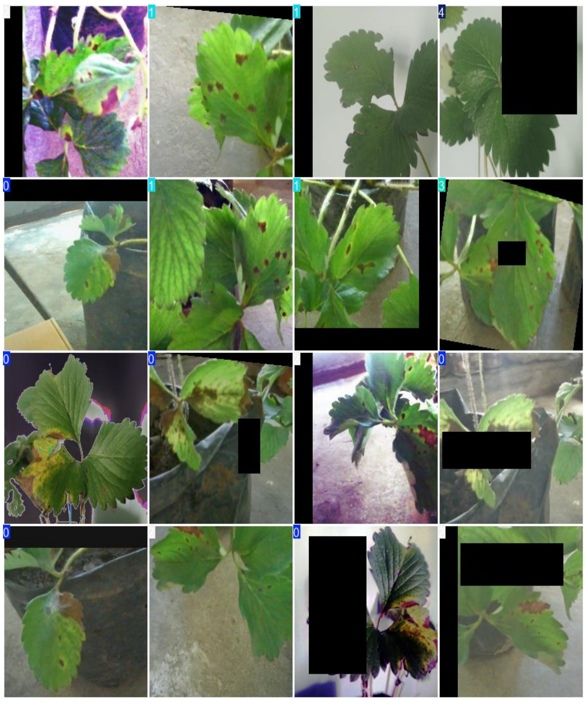


Figure 7. Sample Dataset with Disease Bounding Boxes

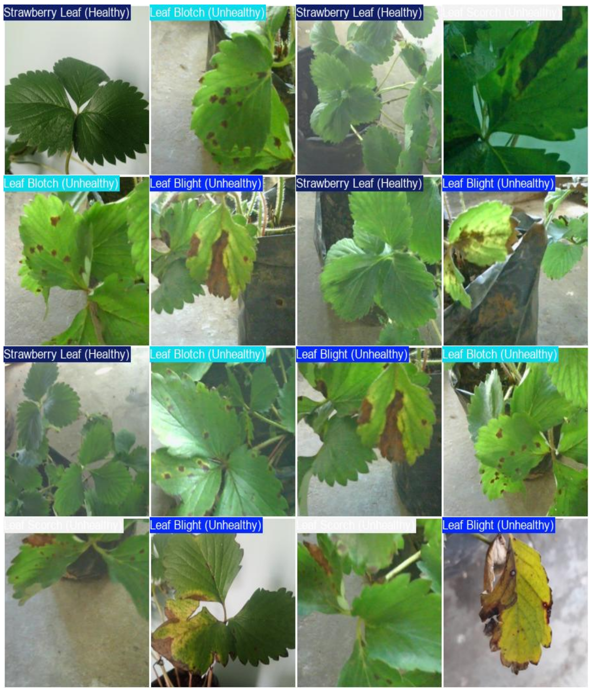
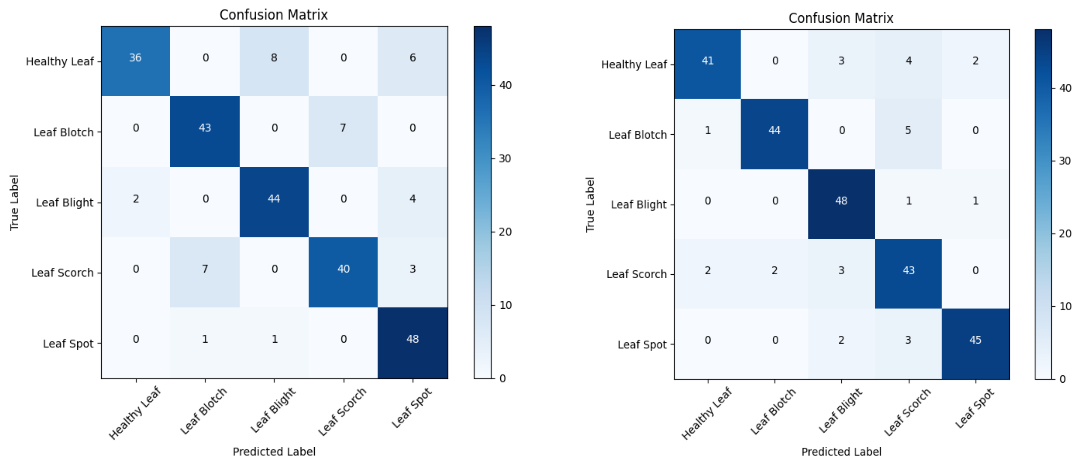


Figure 8. Predicted Class Labels For Validation Images - YOLOv8

D. Experimental Setup and Performance Evaluation

This section details the experimental setup for evaluating the performance of the Inception V3 and YOLOv8 models using custom datasets. The experiments were conducted on a system equipped with Windows 10 OS, an Intel Core i3 processor, and 4 GB of RAM. The development environment included Python 3.9.19, with the PyTorch framework for model implementation and OpenCV 4.1.1 for image processing tasks.

The experiment used a batch size of 16, 20 epochs, a learning rate of 0.01, and the AdamW optimizer. The dataset was split into 70% training, 20% validation, and 10% testing to evaluate model performance on unseen data. In Figure 9, the confusion matrices provide valuable insights into the classification performance of the Inception V3 and YOLOv8 models. Figure 10 and 11 show the predictions made by the Inception V3 and YOLOv8 models, respectively.



(a) (b)

Figure 9. Confusion Matrix (a) Inception V3 Model, and (b) YOLOv8n Model

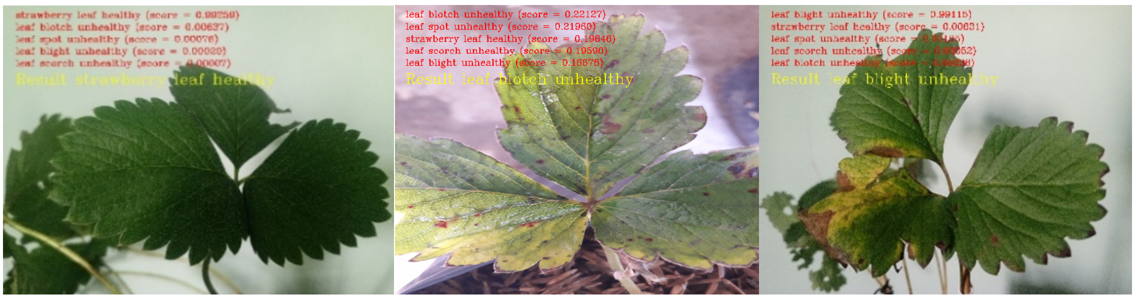


Figure 10. Prediction Results on Inception V3

Figure 11. Detection Results on YOLOv8n

The key evaluation metrics for object detection algorithms include detection accuracy, model complexity, and detection speed. Detection accuracy is primarily evaluated using metrics such as accuracy, precision (P), recall (R), F1-score, and mean average precision (mAP). The following equations can be used to calculate these metrics [14][20].

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \quad (2)$$

$$Precision = \frac{TP}{(TP + FP)} \quad (3)$$

$$Recall = \frac{TP}{(TP + FN)} \quad (4)$$

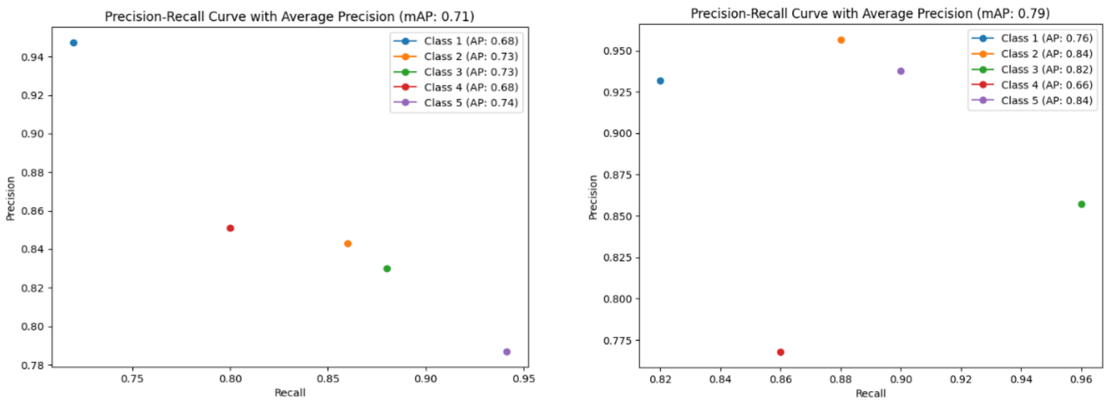
$$F1\text{-}score = \frac{2 \times Precision \times Recall}{(Precision + Recall)} \quad (5)$$

$$mAP = \frac{1}{N} \sum_{i=1}^{N} AP_i \quad (6)$$

Here, TP represents True Positives, FP represents False Positives, FN represents False Negatives, AP stands for Average Precision, mAP refers to Mean Average Precision, and N denotes the Number of Classes.

E. Result and Discussion

This section provides a comparative evaluation of Inception V3 and YOLOv8 for strawberry plant diseases classification. Figure 12 illustrates the precision and recall curves for each disease in the dataset, while Figure 13 highlights the average accuracy in detecting the five strawberry leaf diseases, as assessed for both models. The results are summarized and analyzed in Table 2.



(a) (b)

Figure 12. Precision and Recall Curves (a) Inception V3, and (b) YOLOv8n Model

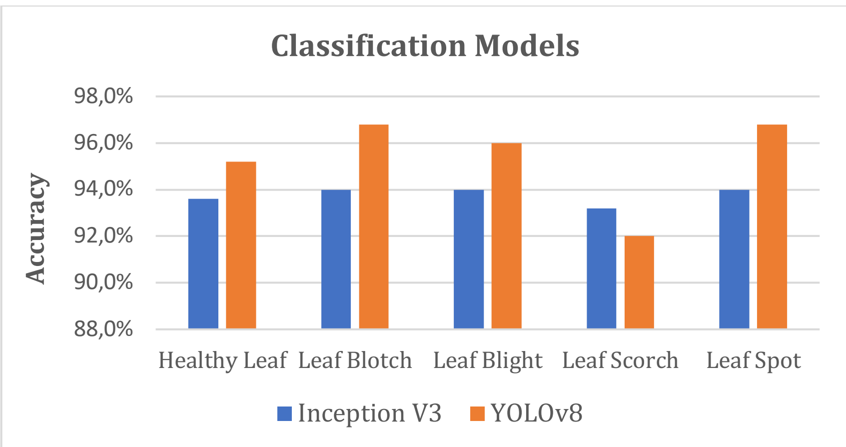


Figure 13. Average Accuracy in Identifying the Five Strawberry Leaf Diseases Using Inception V3 and YOLOv8 Models

Table 2. Summary of Results

Metric	Inception V3	YOLOv8
Accuracy	93.8 %	95.4 %
Precision	86 %	89 %
Recall	84 %	88 %
F1-score	84 %	89 %
mAP	71.5 %	78.6 %
Inference Time (per image)	370 ms	10 ms
Model Size	103.9 MB	12 MB

The custom dataset, thoroughly balanced over 20 epochs, ensured unbiased model learning and robust performance evaluation. It consisted of 5,192 images, which were used for training and testing the models.

- YOLOv8 outperforms Inception V3 with higher accuracy (95.4 %), precision (89 %), recall (88 %), and F1-score (89 %). Its small size (12 MB) and fast inference (10 ms per image) make it ideal for real-time applications where speed and efficiency are critical.
- In comparison, Inception V3 achieves 93.8% accuracy and excels at identifying diseases with distinct visual features, such as leaf scorch. However, it has lower performance metrics (precision: 86 %, recall: 84 %, F1-score: 84 %) and is slower (370 ms per image), with a larger file size (103.9 MB), making it less suitable for time-sensitive tasks.

F. Conclusion

This study compares Inception V3 and YOLOv8 for strawberry plant disease detection, using the AdamW optimizer with a learning rate of 0.01 for 20 epochs. Both models classify diseases and detect bounding boxes of infected areas. YOLOv8 outperforms Inception V3 with 1.6 % higher accuracy (95.4 % vs. 93.8 %) and better precision, recall, F1-score, and mAP. It is also 37 times faster and 8.7 times smaller, making it more suitable for real-time and resource-constrained applications. While both models show high accuracy and efficiency, YOLOv8 excels in performance and computational resource usage. This approach has demonstrated high accuracy in plant disease detection, including the identification of early-stage symptoms undetectable by the human eye. Thus, YOLOv8 is used to address these problems in cases where computational resources play a vital role.

Further research will focus on integrating these models into real-world agricultural applications to enhance disease management and crop yield.

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H. References

[1] K. Tyagi, S. Vats, D. V. Vashisht, "Implementing Inception V3, VGG-16 and VGG-19 architectures of CNN for medicinal plant leaves identification and disease detection", J. Electrical Systems 20-7s, pp. 2380-2388, 2024.

[2] M. Yaseen, "What is Yolov8: an in-depth exploration of the internal features of the next-generation object detector", arXiv:2408.15857v1, 28 Aug 2024.

[3] J. R. Xiao, P. C. Chung, H. Y. Wu, Q. H. Phan, J. L. A. Yeh, and M. T. K. Hou, "Detection of strawberry diseases using a Convolutional Neural Network," Plants, vol.10, no.1, pp.1–14, 2021, https://doi.org/10.3390/plants10010031.

[4] D. A. Pramudhita, "Strawberry plant diseases classification using CNN based on MobileNetV3-large and EfficientNet-B0 architecture", Jurnal Ilmiah Teknik Elektro Komputer dan Informatika (JITEKI), ISSN: 2338-3070, vol. 9, no. 3, pp. 522-534, September 2023.

[5] Q. T. Lu, "An approach for classification of diseases on leaves", (IJACSA) International Journal of Advanced Computer Science and Applications, vol. 14, no. 10, 2023, pp. 1065- 1071, www.ijacsa.thesai.org.

[6] A. Gehlawat, Pankaj, "A comparative analysis of different CNN models for plant disease detection and classification", IJARCCE, vol. 13, Issue 6, June 2024, https://doi.org/10.17148/IJARCCE.2024.13616, ISSN (O) 2278-1021, ISSN 2319-5940.

[7] M. J. Jhatial, R. A. Shaikh, N. A. Shaikh, S. Rajper, "Deep learning-based rice leaf diseases detection using Yolov5", SJCMS, P-ISSN: 2520-0755, E-ISSN: 2522-3003, vol. 6, no. 1, January – June 2022.

[8] H. M. Zayani: "Deep learning for tomato disease detection with YOLOv8", Engineering, Technology & Applied Science Research, vol. 14, no. 2, pp. 13584-13591, 2024, www.etasr.com.

[9] A. Alshammari," A Convolutional Neural Network for detecting Tuta Absoluta effects in tomato crops using YOLOv8", Journal of Electrical Systems, pp. 4241-4247, 2024.

[10] O. I. Villanueva, "Disease identification in crop plants based on Convolutional Neural Networks", (IJACSA) International Journal of Advanced Computer Science and Applications, vol. 14, no. 3, pp. 519-528, 2023, www.ijacsa.thesai.org.

[11] A. Raju and S. Thirunavukkarasu, "Convolutional Neural Network demystified for a comprehensive learning with industrial application," Dynamic Data Assimilation - Beating the Uncertainties, pp. 1-17, 2020, https://doi.org/10.5772/intechopen. 92091.

[12] L. Alzubaidi et al., "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," J Big Data, vol. 8, no. 1, 2021, https://doi.org/10.1186/s40537-021-00444-8.

[13] M. Lambat, R. Kithari, "Plant disease detection using Inception V3", International Research Journal of Engineering and Technology (IRJET), vol. 09, Issue:06, June 2022, www.itjet.com.

[14] D. Tirkey, K. K. Singh, S. Tripathi, "Performance analysis of AI-based solutions for crop disease identification, detection, and classification", Smart Agricultural Technology, 2023, https://doi.org/10.1016/j.atech.2023.100238, www.journals.elsevir.com.

[15] B. Balaji, T. S. Murthy, R. Kuchipudi, “A comparative study on plant disease detection and classification using deep learning approaches”, I.J.Image, Graphics and Signal Processing, pp. 48-59, 2023, https://doi.org/10.5815/ijigsp.2023.03.04, www.mecs-press.org .
[16] D. C. Trinh, A. T. Mac, K. G. Dang et al.; “Alpha-EIOU-YOLOv8: an improved algorithm for rice leaf disease detection”, AgriEngineering, pp. 302–317, 2024, https://doi.org/ 10.3390/agriengineering6010018.
[17] D. Xie, W. Yao, W. Sun and Z. Song, “ Real-time identification of strawberry pests and diseases using an improved YOLOv8 Algorithm”, Symmetry, 1280. 2024, https://doi.org/10.3390/sym16101280.
[18] B. Ahmad et al., “Efficient real-time detection of plant leaf diseases using YOLOv8 and Raspberry Pi”, VFAST Transactions on Software Engineering, vol. 12, Issue 2, pp:250-25, 2024, https://doi.org/10.21015 /vtse.v12i2. 1869.
[19] M. Babadoost, “Strawberry leaf diseases”, Report on Plant Disease, Department of Crop Sciences, University of Illinois at Urbana-Champaign (217-333-1523; email: babadoos@uiuc.edu).
[20] A. Tasnim, Md. Saiduzzaman, M. A. Rahman, J. Akhter, A. S. M. M. Rahaman, “Performance evaluation of multiple classifiers for predicting fake news”, Journal of Computer and Communications (JCC), vol. 10, no. 9, DOI: 10.4236/jcc.2022.109001, 2022, https://www.scirp.org/journal/jcc.