

Eggplant Leaf Disease Classification Using Deep Learning and a Robust Real-Time System Based on YOLOv8 and Streamlit

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ABSTRACT

Early disease Classification will help reduce crop loss as well as increase agricultural productivity. A rapid and accurate deep learning-based framework to identify different diseases in eggplant on the marketplace level has been proposed in the research. Implementation and Training of an End-to-End Object Classification Based on YOLOv8. To train a custom multi-class data set, six target classes: Healthy Leaf, White Mold Disease, Leaf Spot Disease, Wilt Disease, Mosaic Virus Disease, and Insect Pest Disease. Initial work was done in developing the object detectors. We used standard metrics like accuracy, precision, recall, and F1-score to evaluate the performance of the model. When it came to finding Plant Leaf Disease (PLD), traceable configurations were revealed from configuration tuning among the combinations of hyperparameters, which converged at equal measurement intervals on a curve between Classification accuracy and computation efficiency from screened candidate architectures along ranges determined by performance metrics defined for detecting plant diseases using only above-ground debris as input sources. With stable convergence during the training phase, the model YOLOv8m had an accuracy of 96.84%, a precision of 96.85%, a recall of 96.84%, and an F1 score of 96.84%. The model that has been trained was deployed with the help of a web application named Streamlit, so that it could be used in practical procedures where disease can be detected if we upload an image. That means the system is robust and operates effectively in the wild as opposed to ideal test conditions, which lends itself well to agricultural usage. The present work provides an integrated, optimized deep learning detector with a user interface beneficial for precision farming that can help in the early identification of diseases on eggplants, resulting in increased yield.

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1. INTRODUCTION

Agriculture is an integral part of fulfilling the increasing food needs worldwide, and thus an accurate assessment of crop health can boost productivity with more yield at less loss. White mold, leaf spot, wilt, mosaic phytovirus, and breeding insect pests are some of the diseases affecting plants in Eggplant (*Solanum melongena*), which is one of the economically important vegetable crops widely cultivated around the world. Also, the accessibility of structured datasets has enabled research in this field by letting us make computer vision-based solutions for disease Classification [1]. If these diseases are detected early, the plant can be preserved, and the spread of the disease can be prevented, which leads to good crop quality and high yield.

Standard methodologies of disease identification are based on manual examination, mostly subjective in nature, laborious, time-consuming to establish, and expert knowledge-dependent. In much of the agricultural world, access to expertise is narrow, limiting accurate diagnosis [2]. Moreover, visually

resembling symptoms within various diseases make them more prone to misclassification. This has led to the automatic patterns for disease Classification. Transfer learning-based approaches to plant disease recognition have been previously investigated, with better performance observed in certain models compared to traditional methods. Likewise, ensemble and fine-tuned deep learning architectures have also been explored for improving classification accuracy on eggplant disease classification tasks [3][4].

Deep learning with computer vision has more recently revolutionized the field of image analysis for plant disease diagnosis. Publicly available convolutional neural networks (CNNs) have been widely utilized for classification purposes, but they lack the capability to localize disease areas. This limitation can be overcome using object Classification models that allow localizing and classifying disease symptoms in a single shot. Models like YOLO and RT-DETR have been successful in agricultural applications, especially when multiple disease patterns are simultaneously present in a complex environment [5].

Among the object Classification methods, YOLO family approaches have become popular over time since they do not require a huge amount of processing and have real-time performance. Lightweight versions like YOLOv5-based models have been proven to work effectively for detecting eggplant diseases without being computationally costly [6]. In this area, recently released YOLOv8 architectures have demonstrated improved accuracy in both Classification and feature extraction [7]. Furthermore, recent studies have built on the basic framework for multi-modal data fusion and attention-based event Classification. They have also examined the circumstances under which the events remain optimal under adversarial challenges [8]. Simultaneously, the studies concentrate on novel early Classification models, improved analysis of diseases, and standard biological analysis. Verticillium wilt Classification, coupled with the use of advanced imaging channels and improved physiological metrics, shows the importance of early disease Classification to inhibit the even greater spread. This proves the need for realistic agricultural conditions to enhance the accuracy of the Classification systems [9].

Based on the recent advancements, the framework extends YOLOv8 and implements multi-class disease Classification on eggplant leaves. The data set modeled six classes, including Healthy Leaf, White Mold, Leaf Spot, Wilt, Mosaic Virus, and Insect Pest, to name a few. The leaf images classified in the data set attest to the prediction of the model being much more accurate and granular than traditional classification. In this research, the proposed framework's performance will be assessed using the YOLOv8 Classification model and several key traditional metrics, including accuracy, precision, recall, and F1-score, to assess the model's results. Overall, the YOLOv8 Classification model proved to have the best training results of all the models tested, with a modular, deployable design and a robust Classification capability [10].

Utilizing a Streamlit-based web app to enhance user experience, the app allows users to upload images with predictions being returned almost immediately. It provides access to farmers and agricultural practitioners without the need for technical skill. It aids in decision-making and thus avoids losses by helping make timely decisions for better crop management. As a result, this work provides a tractable and effective methodology for eggplant disease identification, incorporating advanced object Classification methods and an easy-to-use deployment environment. Inclusion of a diagnostic assay validated for simultaneous identification and management of disease would assist the expanding market for precision agriculture by providing farmers, extension agents, and researchers with an accurate early Classification tool.

1.1. Contributions of the Study

- Created and populated a multi-class database of eggplant leaf images with six groups: Healthy Leaf, White Mold Disease, Leaf Spot Disease, Wilt Disease, Mosaic Virus Disease, and Insect Pest Disease.
- Created and developed an end-to-end deep learning framework using YOLOv8 architecture for the classification of various eggplant leaf diseases with high accuracy.
- Evaluated performance rigorously with standard metrics and reported state-of-the-art scores.
- Chosen YOLOv8m as the best configuration; the best combination of Classification performance and speed from all models tested under Implicit Violation Inclusion
- Built and deployed a web application based on Streamlit that allows anyone to upload pictures of their eyeglasses, allowing us to diagnose the disease with minimal user interaction using an image.
- Provided a real-time, precise, and accurate eggplant leaf disease diagnosis that is practical and scalable to help with precision agriculture.

2. RELATED WORKS

Based on image analysis, the automated Classification of plant diseases has been considerably improved due to recent advances in deep learning-targeted computer vision. Different methods for accurate and real-time disease identification have been explored, such as Transfer learning, CNN, YOLO, and Real-

Time Classification Transformer (RT-DETR). This section summarizes the previous works done in terms of eggplant disease Classification, indicating a few key methods used and their limitations.

In recent years, crop disease Classification using deep learning has attracted attention thanks to its potential to automate diagnosis and improve agricultural productivity. Access to good-quality datasets is one of the most basic challenges within this space. To fill in this gap, a large dataset for eggplant leaf diseases has been created under laboratory and field conditions. Moreover, the VGG16 architecture was employed with different color space transformations and had an accuracy of 99.4%. This study defined the time and more object-oriented datasets for improving model performance [11].

Extending dataset-driven methods [12], a few studies have suggested using more sophisticated deep learning architectures to classify diseases. A two-stream deep fusion model that combines the CNN-SVM and CNN-Softmax pipelines was developed for nine eggplant diseases identified in [13]. Our model outperformed some classical architectures like VGG16, ResNet50, and MobileNet with higher accuracy and lower false positive scores. In a similar domain, ensemble learning methods have also been explored for improving classification robustness. We proposed a weighted ensemble of ConvNeXt, DenseNet, and EfficientNet that performs well on datasets with different class distributions. An analogous ensemble-based approach was proposed in [14], which focuses on a new adaptive feature fusion that enhances both the generalization and stability.

There has been a recent trend that has also catered to the rapid Classification of real-time agricultural models [15]. A lighter YOLOv8-based model with improvements like FasterNet, attention modules, and optimized loss functions was proposed in [16], achieving an mAP of 92.61% as well as high Classification speed. Instrumentally, a new architecture was proposed, amalgamated with a YOLOv8n-based model, which is reintegrated with transformer-based modules and dynamic convolution operations to enhance the Classification accuracy of these models in complex environments [17]. An optimized YOLOv8 framework was used in another study [18] for real-time Classification of eggplant seedlings, which presented higher accuracy and inference speed while reducing the complexity of models.

In addition to object Classification, some researchers studied attention mechanisms and feature enhancement schemes to further improve mIoU. The CBAM-EfficientNetB0 Model achieved the best classification accuracy of 98.7%, greatly outperforming baseline architectures. Moreover, modal fusion-based methods have been proposed to increase the robustness of Classification results. Proposed a technique using data fusion and an attention mechanism, which could distinguish eggplant diseases across different backgrounds with better performance [19]. Additionally, recent studies have been centered around the early Classification of disease. To detect verticillium wilt at the early stage, a deep learning method based on multi-channel image fusion has been developed, and multispectral imaging and deep learning have been used in [20] for identifying the pre-symptomatic condition of the disease with high accuracy. Additional biological studies correlated these environmental factors to disease incidence, giving insight into the importance of subsequent progression and prediction of disease onset. This underlines the value of combining environmental and imaging data in the holistic management of disease [21].

Eggplant disease Classification was also explored using traditional machine learning and hybrid approaches. Encouraging accuracy using feature fusion methods with DCNN and RBFNNs for disease classification is accomplished through [22]. Likewise, in another work, image processing methods including segmentation and feature extraction based on wavelets, combined with the use of artificial neural networks for classification purposes. While these methods work well, they often rely on heavy preprocessing and a manual feature design stage [23]. New techniques, such as federated learning, have also been introduced, aimed at tackling issues of data privacy and scalability. A federated CNN-based method for disease severity classification was also proposed in [24], which enables large-scale generalization by applying a federated mechanism where genomic datasets are stored separately. More specifically, for example, a few survey works reviewed the contribution of machine learning and artificial intelligence on the approach used for plant disease Classification and highlighted the potential gaps to develop real-time monitoring systems as a scalable solution suitable for modern agriculture [25].

Even with this progress, the existing approaches still have some limitations. Several studies mainly focus on image classification rather than object Classification and are unable to localize disease regions in an image. Although accurate, ensemble and multimodal methods incur a high computational cost, which makes their deployment for real-time applications infeasible. Likewise, better object Classification models may attain a good accuracy but utilize complicated architectures that are hard to deploy in real-life situations. Moreover, some methods are dependent on controlled datasets or practiced in specific environmental conditions, which results in less generalization to practical scenarios.

Because of the restrictions around making scalable, high-performing models and user-friendly deployment platforms work closely. Although some studies show good experimental outcomes, few consider the practical usability for farmers and other agricultural practitioners. Immediate availability and simplicity for field applications continue to be key points regarding the uptake of this type of technology. To close these

gaps, the current study proposes an end-to-end system based on deep learning using the YOLOv8 framework for multi-class eggplant disease classification. Unlike approaches based on classification, the proposed method allows for localizing and identifying regions of disease. The system strikes a fine balance between the cost of computation and the accuracy of Classification and allows for the selection of the YOLOv8m model tailored to real-time worksites. Also, including a model as a Streamlit web application greatly enhances the convenience and flexibility of on-demand disease Classification for users with limited domain expertise. The aim of this research is to improve the levels of Classification performance to approximate the research available for use in agriculture. The system reduces the subjection to human assessment and aids in the early Classification, reliability, and scalability of precision farming.

3. RESEARCH METHODOLOGY

This section outlines the framework and generalized steps for detecting diseases in eggplant leaves. These include the preparation of datasets, the model structure, and training and evaluation. The methodology suggests the use of a YOLOv8-based model for the Classification and diagnosis of eggplant diseases. It further describes the Streamlit-based application deployment to support real-time diagnosis and prediction.

Table 1. Diseases of the eggplant leaf with sample photos

Disease Name	Description
Healthy Leaf	Deep green leaf showing neither discoloration, spots or damage Shows normal plant growth and no disease.
White Mold Disease	Leaf surface infected with a fungal disease displaying white, cottony growth. Usually observed in humid environments and may lead to decay of the tissues.
Leaf Spot Disease	Round dark brown or black spots on leaves that can expand and dry out leaf tissue.
Wilt Disease	Interruptions in the transport system of plants that cause the leaves to droop, turn yellow and dry out.
Mosaic Virus Disease	Causes mottled yellow-green patches and leaf curling as well as growth and yield loss.
Insect Pest Disease	Holes, eaten edges, and blotchy discoloration from aphids or caterpillars.

Table 1 shows a list of the eggplant leaf disease classes considered in this work, their descriptions, and sample images. The classes, which consist of healthy leaves and five primary disease categories, are categorized separately. These descriptions provide a recap of the primary symptoms with visible characteristics for each disease: discoloration, spots, fungal growth, and structural damage. Furthermore, images of each class that demonstrate the variation and visual patterns in the dataset are shown. Such variances are essential to train a deep learning model in distinguishing between types of diseases accurately. Furthermore, the table provides clarity in understanding what is inside our dataset and helps replicate the proposed methodology.

Table 2. Comparison of YOLO Models Development and Reasons for Choosing YOLOv8

Category	YOLO Version	Key Features	Limitations	Applications
Early Models	YOLOv1	First real-time single-stage detector	Low precision, Classification of smaller objects is weak	Basic object Classification

	YOLOv2 (YOLO9000)	Batch normalization, multi-scale training	Limited feature extraction capability	General object Classification
	YOLOv3	Multi-scale prediction, Darknet-53 backbone	Increased complexity, slower than v2	Complex scene Classification
Intermediate Models	YOLOv4	The CSPDarknet Backbone with improved Speed & Accuracy	Complex architecture, harder to tune	Real-time applications
	YOLOv5	Easy implementation, scalable models	Released unofficially from authors of original YOLO	Research and industry use
Advanced Models	YOLOv6	Optimized for industrial deployment	Less flexible for customization	Industrial systems
	YOLOv7	High accuracy and efficient training	High computational requirements	High-performance Classification
Modern Models	YOLOv8	Anchor free Classification, fully improved feature extraction, support for Classification + classification	Requires hyperparameter tuning	Real-time AI, agriculture, medical imaging
	YOLOv9	Enhanced feature aggregation and generalization	Still evolving, limited benchmarks	Advanced Classification tasks
	YOLOv10	Reduced latency, optimized architecture	Limited adoption	Real-time systems
	YOLOv11	Improved efficiency and accuracy	New model, less validation	Research applications
	YOLOv12	Advanced optimization techniques	Experimental stage	Cutting-edge research

YOLO (You Only Look Once) family of models has become increasingly more accurate and faster with each iteration, touching on architecture improvements from YOLOv1 to the latest version in Table 2. The early versions, like YOLOv1 and YOLOv2, provide real-time object Classification but with less accuracy and feature extraction quality. Later versions, such as YOLOv3 and YOLOv4, featured multi-scale Classification and feature-level representation, but also became more computationally expensive. Later intermediate and advanced versions: YOLOv5, YOLOv6, and YOLOv7 further improved Classification performance and scalability to a level of industrial applications in terms of both performance, usability, and robustness. However, such models require much more computing power or fine-tuning. The state of the art in modern models is YOLOv8, recognized due to its anchor-free Classification mechanism with CSPNet for better feature extraction and a simplified architecture. The training process also includes the classification of problems in a seamless manner with a high level of competition. YOLOv8 and newer models like YOLOv9–YOLOv12 are less stable and have fewer real applications that properly validate performance, meaning YOLOv8 had better overall validation. Based on these reasons, this work proposes the use of YOLOv8 as a precision agriculture application that offers a high degree of real-time eggplant disease Classification, a trade-off between accuracy and performance, as well as ease of use in its deployment.

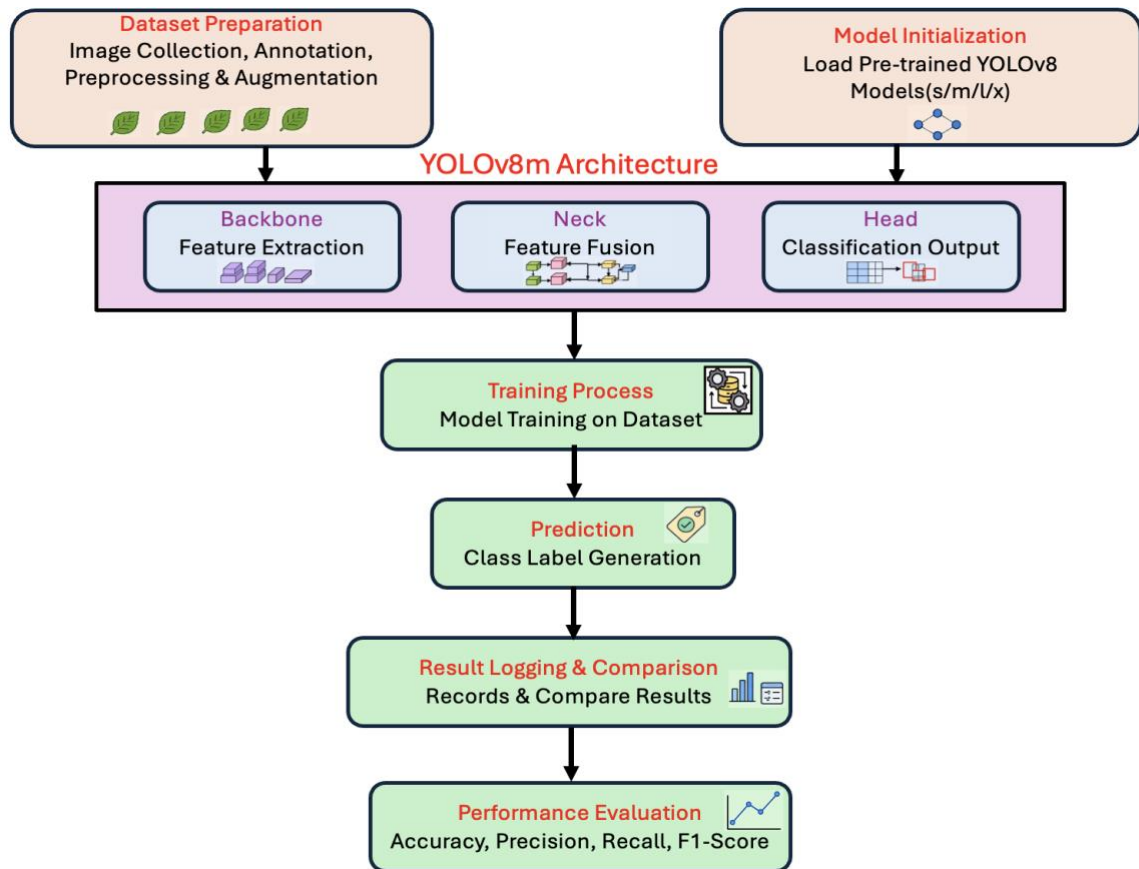


Figure 1. YOLOv8m multi-class eggplant leaf illness Classification technique

Figure 1. The proposed YOLOv8m eggplant leaf disease Classification system has three stages: preparation, implementation, and application. Dataset preparation starts with collating images of eggplant leaves and annotating boxes around all discerned objects. Images are also pre-processed with augmentation methods to assist the model's generalization. Model initialization occurs when YOLOv8 pre-trained weights are loaded and the architecture of YOLOv8m is built. The basic Classification framework consists of three parts: the neck, which combines the multi-scale feature representations, and the head, which provides the classification and localization of objects. Finally, the dataset, now annotated, can be used to train the model to predict and classify diseased regions of the eggplant leaf. Once the training is completed, the prediction phase consists of writing disease class labels for the recognized diseased regions of eggplant leaves. These results are input to the result logging and comparison phase, where predictions are logged and evaluated against the ground truth. Finally, we evaluate the system using standard metrics: accuracy, precision, recall, and F1-score, which tell how well the proposed model is performing. The developed pipeline enables fast, accurate, and real-time Classification of multiple eggplant leaf diseases for on-field applications in precision agriculture.

Table 3. Distribution of the Eggplant Leaf Disease Dataset

Class	Training	Testing	Validation
Healthy Leaf	7265	2179	2179
White Mold Disease	315	94	94
Leaf Spot Disease	3010	903	903
Wilt Disease	325	97	97
Mosaic Virus Disease	6710	2013	2013
Insect Pest Disease	2728	818	818

Table 3 indicates the distribution of samples in each class created by different eggplant leaf conditions from the dataset hosted on IEEE DataPort. Since we made use of YOLOv8 models, the dataset was split into training, testing, and validation subsets. It takes six classes: healthy leaf, white mold disease, leaf spot disease, wilt disease, mosaic virus disease, and insect pest. The data contains both healthy and diseased leaf images that can be used for classification or Classification. It can identify image patterns correctly as it is extracting features concerning each class, and it contains more images than any other in the training set. Monitor and tune parameters on the validation set, but only measure performance on unseen data with the testing set. The dataset samples for some classes, like Healthy Leaf and Mosaic Virus Disease, far outweigh other classes such as White Mold Disease and Wilt Disease, which has created a class imbalance in the data, as shown in the following table. The distribution/imbalance in the data can also hamper model efficiency; we have tackled methods like augmenting and class weighting. Overall, this structure of the data set complies with the standard YOLOv8 Workflow, which helps maintain a consistent use case for training, validation, and testing so you can get started on model building.

3.1. Dataset Preparation

We used a dataset that contains a few eggplant leaf images with proper labels, divided into six classes. Formally, the dataset consists of a set of input–output pairs defined as in equation (1).

$$D = \{(x_i, y_i)\}_{i=1}^N \quad (1)$$

Here, x_i is the i^{th} image and y_i is the corresponding label. N is the number of images, and each image falls in one of the six disease categories, $K=6$.

$$x_i \in \mathbb{R}^{H \times W \times C} \quad (2)$$

In equation (2), H is the height of the image, W is the width of the image, and C is the number of color channels, which in this study are the three channels of RGB. The representation of the images enables the model to learn spatial and color-based features that are critical in distinguishing different patterns of diseases. As represented in Equation (3), each image in the case studies has a corresponding disease.

$$y_i \in \{1, 2, \dots, K\} \quad (3)$$

In this representation, K is the number of classes. For this representation, we can say that Categorical y_i represents the y_i^{th} class from the K total classes of the system. To get from the modeling layer to the application layer, the classes are represented in the form of one-hot encoding, as shown in equation (4).

$$y_i = [y_{i1}, y_{i2}, \dots, y_{iK}] \quad (4)$$

This then allows us to say that y_{ik} the image is a case of the class; otherwise, it is not (i.e., $y_{ik} = 1$ or $y_{ik} = 0$). As stated, the representation allows for the application of the probabilistic loss functions to the system during the optimization. The input images are subject to a minor transformation, as stated in equation (5), to increase the likelihood that the model does not overfit.

$$x'_i = T(x_i) \quad (5)$$

In this case, $T(\cdot)$ indicates the transformation function applied to the original image data. The transformation function, in this case, involves a sequence of operations, as described in Equation (6).

$$T(x) = T_{flip}(T_{rot}(T_{HSV}(x))) \quad (6)$$

With this formulation, it is understood that, in the transformation of an input image, a set of operations of flipping, rotating, and adjusting the image to the hue-saturation-value color space is performed. Such operations help address the model's performance in different orientations and lighting conditions and image degradation caused by atmospheric phenomena. Therefore, the training is expressed, considering the transformed training set, as equation (7).

$$\min_{\theta} \mathbb{E}_{(x,y) \sim D} [\mathcal{L}(f(T(x); \theta), y)] \quad (7)$$

Where, in this case, $f(x; \theta)$ is the deep learning model, and L is the loss function. Specifically, Equation (7) implies that the model should minimize the expected loss, concerning not only the original samples but also the augmented samples, thus enhancing robustness and improving classification. Therefore, considering the equations from (1) to (7) and their respective sequence of operations, a comprehensive augmented training dataset aimed at improving the learning of the model concerning the disease-related features in the eggplant leaves is proposed.

3.2. Model Initialization

In order to be more effective and use less learning time, pre-trained YOLOv8 classification models are used. YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x models are chosen, each with a different degree of model depth and complexity. Transfer learning involves loading weights that have been learned on additional, large datasets and initializing these models.

$$\theta = \theta_{pretrained} \quad (8)$$

Let θ be the parameter set for the study model and $\theta_{pretrained}$ be the parameters from a large benchmark dataset. Equation (8) shows the process of embedding learned representations like the edges, textures, and shapes of the images. This process speeds up training as it provides a starting point for the pre-trained model on the eggplant disease data. Since the feature representations pre-trained on external data show the model where it should end up, the optimization process becomes more isotropic and requires fewer epochs to reach the desired model function. Also, the approach entails fine-tuning the pre-trained parameters with a data set for the target tasks.

$$\theta^* = \arg \min_{\theta} \mathcal{L}(f(x; \theta), y) \quad (9)$$

Here, the set of parameters optimized after training is the model, and $\mathcal{L}$ denotes the loss function. Equation (9) suggests that the pre-trained parameters are fine-tuned with respect to classification error on a new dataset. Model initialization as per Equation (8), and then after that, optimize this as per Equation (9). The proposed method converges faster with more accuracy and generalizes better. This makes transfer learning with YOLOv8 an excellent choice for eggplant leaf disease classification when the datasets cannot be as large as the benchmarks of a larger scope.

3.3. YOLOv8m Architecture

The YOLOv8m architecture is composed of three main components: first, the Backbone, second, the Neck, and finally, the Head. These parts operate in a pipeline, simplifying the extraction of features, fusing multi-scale information, and exporting classification outputs. The backbone performs the steps of extracting deep feature representations from the input image.

$$z_b = f_b(x; \theta_b) \quad (10)$$

Here x is the input image, $f_b(\cdot)$ the backbone network, θ_b are the learnable parameters of the backbone, and z_b is its feature map. As defined in Equation (10), given the raw input, the backbone will convert the input into a salient representation that captures spatial patterns, including edge textures and disease specificity. Next, the neck integrates features from different scales by fusing multiple scales to improve its representation capacity.

$$z_n = f_n(z_b; \theta_n) \quad (11)$$

Here $f_n(\cdot)$, instead of the neck module, parameters are provided θ_n . The produced output z_n incorporates enhanced feature representations, combining low-level and high-level features. As described in Equation (11), at the same stage, it enhances the model learning towards both fine-grained and global patterns for better highlighting to identify relevant disease changes from various leaf images. The fused features are then passed on to the head, which outputs the final classification.

$$z = f_h(z_n; \theta_h) \quad (12)$$

Here, $f_h(\cdot)$ the classification head θ_h is its parameters, and z is the vector of logits for each class. According to Equation (12), the head maps the fused features to class-specific scores, which get translated

into probabilities. Combining these three elements, the model can be constructed as a function of composition.

$$f(x; \theta) = f_h(f_n(f_b(x))) \quad (13)$$

Here $\theta = \{\theta_b, \theta_n, \theta_h\}$ corresponds to each of the model parameters. Equation (13) represents the sequential flow of picture processing starting from the input image to the last resulting output, including feature extraction, feature fusion, and the classification process. The layered structure assists the YOLOv8m model in learning the various levels of image representations to identify features and leaf patterns of the eggplants. The Backbone component extracts essential features, the neck improves the representation of features, and the head accomplishes significant classification, resulting in superior Classification capabilities.

3.4. Classification and Probability Estimation

The classification head of YOLOv8m yields a vector of logits, with each entry corresponding to a disease class. The logits then undergo softmax activation, resulting in normalized probabilities.

$$P(y = k|x) = \frac{e^{z_k}}{\sum_{j=1}^K e^{z_j}} \quad (14)$$

Here, $P(y = k|x)$ represents the predicted probability that the image x belongs to the class k , and z_k refers to the logit pertaining to class k in a total of K classes. The denominator of (14) constitutes the sum of the exponentials of the class logits, and thus the predicted probabilities are bound to $[0,1]$.

The inverse of Equation (14) is that the softmax function inherently transforms raw outputs from the model into more comprehensible probability distributions. A higher logit value will yield a high probability score, signifying higher confidence in the class prediction. This enables the model to give probability scores for several different disease classes. The top class with the highest probability value gives us the final predicted class. This process is expressed as equation (15).

$$\hat{y} = \arg \max_k P(y = k|x) \quad (15)$$

Here $\hat{y}$ represents the predicted class label. The model classifies the input image with respect to the class that it estimates is more probable. Two key advantages are provided by the Softmax function in the case of multi-class classification. So first, it provides numerical stability and normalized output values like predicted probabilities. Second, it supports efficient optimization using probabilistic loss functions such as categorical cross-entropy at training time. These features enhance the model in learning discriminative feature representations to classify eggplant leaf diseases correctly.

3.5. Loss Function

YOLOv8m classification model is trained with a categorical cross-entropy loss function, which can be defined as the difference between the predicted probability distribution and the true class labels. The loss for a single training example is given by equation (16).

$$\mathcal{L} = - \sum_{k=1}^K y_k \log(P(y = k|x)) \quad (16)$$

Here, K is the classification task, y_k is the ground truth for class k , and $P(y = k|x)$ is the predicted probability from the Softmax function in Equation (14). In Equation (16) $y_k=1$ if that class is the correct class, and otherwise 0. One with its logarithm term that penalizes a poor prediction.

The categorical cross-entropy loss measures how well the predicted distribution indicates the actual one. When the value of predicted probability for the correct class gets to 1, then this means the loss becomes small, and vice versa. On the other hand, if the predictions are not correct, then the loss value will be higher, so the model needs to make changes to its parameters. The overall loss is calculated as the average of sample losses for the entire dataset, as represented in equation (17).

$$\mathcal{L}_{total} = \frac{1}{N} \sum_{i=1}^N \mathcal{L}_i \quad (17)$$

Here, N is the number of training samples, and $\mathcal{L}_i$ is the loss on the i^{th} sample. Since we want optimization not to be biased towards individual samples, it encourages performance across all training samples. Training aims at minimizing the total loss introduced and thus increasing the classification ability of

the model. The YOLOv8m model can learn discriminative features with increasing accuracy for classifying eggplant leaf diseases by continuously reducing the loss value during training.

3.6. Model Training

The goal of the training is to find model parameters that minimize the total loss function. Here θ^* are the best model parameters after training, and the total categorical cross-entropy loss is denoted as $\mathcal{L}_{total}$. In fact, Equation (18) tells the training process to find some values of parameters so that the whole dataset has a smaller classification error.

$$\theta^* = \arg \min_{\theta} \mathcal{L}_{total} \quad (18)$$

This optimization is achieved using the general gradient-based learning approach. Gradient descent, as defined in Equation (19), is used iteratively to update the parameters of the model. Here, θ_t indicates the parameter values at iteration t, and so on, θ_{t+1} are the updated parameters, η is the learning rate, and $\nabla_{\theta} \mathcal{L}$ is obtained from the losses as gradients related to model parameters. Gradient gives us information on how to change our parameters so that our loss will decrease.

$$\theta_{t+1} = \theta_t - \eta \nabla_{\theta} \mathcal{L} \quad (19)$$

The learning rate determines the size of parameter updates during optimization. Finding an appropriate learning rate leads to good convergence, preventing the training from diverging or converging too slowly. The gradients are being calculated and backpropagated for each iteration, so the model can learn and extract important and discriminative features from the training data on its own. The training in this study was done for 20 epochs on the augmented data samples created by flipping and rotating images, as well as HSV transformation. Using augmented information supplies better scale power as it lowers the network in unique rotations, lighting, enabling YOLOv8m to generalize very well to unseen eggplant leaf images and have a better classification performance in real-state applications. The model gradually reduces the loss function as it progresses through training and enhances the accuracy of predictions. This entire optimization is passed down to a trained model that can discriminate between healthy and diseased eggplant leaves.

3.7. Prediction

Once the training process is finished, the YOLOv8m model categorizes given input images into one of the disease categories. Given an input image x, the model computes probability scores for all possible classes by applying the Softmax function shown in Equation (14). The final predicted class gets calculated, and it picks the class that is highest in probability.

$$\hat{y} = \arg \max_k P(y = k|x) \quad (20)$$

Here $\hat{y}$ is the predicted class label, $P(y = k|x)$ is the probability that the input image belongs to class k, and K is the number of classes. In Equation (20), the class corresponding to the highest probability value among all predicted classes is identified. During the prediction process, the test image is passed through the trained YOLOv8m network along with large-scale feature extraction, followed by multiplied feature fusion and classification. For each category, the model calculates confidence scores, and the classes that have the highest confidence scores are predicted. This way, the model can identify healthy and diseased eggplant leaves based on what it learned visually. The prediction method takes the maximum probability value. This helps achieve further consistent and understandable results. The predicted class label is applied for disease diagnosis in the running real-time application.

3.8. Result Logging and Comparison

The performance of each model variant is logged and evaluated based on standard classification metrics. In our work, we establish the metrics of evaluation in Equation (21)

$$R = \{Accuracy, Precision, Recall, F1_Score\} \quad (21)$$

In this case, R is the set of computational metrics and defines the model classification score. In equation (21), the R metrics offer insight into a model's potential and overall performance based on multiple angles. The Accuracy metric is focused on answer correctness across the entire output set. Precision is based on the correctness of the positive predicted cases. Recall is modeled based on the sensitivity of the model to

identify all of the diseased aspects, and the F1_Score is meant to quantify the balance of Precision and Recall. Collectively, the R metrics offer a summary and ample insight into model performance across all classification levels of the various diseases. After every single epoch of training, evaluations get logged for the YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x model combinations. The training runs record evaluations in log files to track performance and analyze combinations. The process of comparison is captured in Equation (22).

$$M^* = \arg \max_M R(M) \quad (22)$$

Here, M denotes a given YOLOv8 model variation, and M^* is used to indicate an optimal model during evaluation. This means that the model with the best overall metric performance is selected as the final configuration. The results allow comparison of various YOLOv8 architectures in terms of accuracy, compute efficiency, and stability while training them. As demonstrated by the experimental results, YOLOv8m was found to be promising in offering an efficient solution combining high-performance accuracy and real-time efficiency for eggplant leaf disease classification.

3.9. Performance Evaluation

The proposed YOLOv8m Model is evaluated based on standard classification metrics such as accuracy, precision, recall, and F1-score. These metrics give a clear idea about how well the model can classify eggplant leaf diseases correctly. Accuracy is the overall percentage of samples that are correctly classified with respect to the total predictions made. Here, TP, TN, FP, and FN refer to true positive prediction, true negative prediction, false-positive prediction, and false-negative prediction, respectively. Equation (23) Accuracy measures the overall correctness of the classification model.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (23)$$

It quantifies the accuracy of positive predictions by measuring how many predicted samples are truly positive; it's the precision. According to Equation (24), we can say that high precision means fewer true positive classifications. High precision in eggplant disease Classification implies that predicted disease labels are very reliable.

$$Precision = \frac{TP}{TP+FP} \quad (24)$$

Recall measures the fraction of relevant disease instances that are identified by the model and is calculated as in equation (25). Recall measures the ratio of true positive samples correctly identified by the model. A higher recall value shows effective Classification of diseased leaf samples with a lesser number of false negatives.

$$Recall = \frac{TP}{TP+FN} \quad (25)$$

F1-score gives out one number by taking the harmonic mean of precision and recall. Equation (26) captures a key evaluation of classification performance on an unbalanced dataset. The F1-score is high only if both Precision and Recall are performing well together.

$$Recall = \frac{TP}{TP+FN} \quad (26)$$

Whichever metric we use, these need to be interpreted in tandem with each other to be able to get a clear understanding of the classification ability possessed by the YOLOv8m model. As suggested in our earlier work, this allows for a comprehensive evaluation of the proposed approach to accurately categorize eggplant leaf diseases.

3.10. Model Selection

We determine the better model by benchmarking YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x. Model selection occurs at this step based on evaluating metrics derived from the experiment, with focus given to the F1 score because it can balance precision and recall contributions represented in equation (27).

$$M^* = \arg \max_M F1(M) \quad (27)$$

Here, M is the set of candidate YOLOv8 models, and $F1(M)$ denotes the F1 score on a specific model. This means that M^* is the model that optimizes F1-score and is bounded by the rest of the variant configurations. To prioritize a model is to maximize the F1-score because it considers false positive and false negative predictions at the same time, compared to accuracy, which considers only the true value of predicted classes. This is especially crucial for multi-class disease classification tasks where maintaining consistent performance across every class is a must-have.

Experimental results show that the YOLOv8m model provides the optimal trade-off between classification accuracy and computational efficiency. Smaller variants, such as YOLOv8n, allow for faster inference speed with lower cost of computation but suffer in terms of classification performance. On the flip side, bigger models like YOLOv8l and YOLOv8x can obtain marginally better accuracy with a substantially larger amount of compute and training time. The YOLOv8m model can achieve stable convergence and high classification accuracy with efficient computational performance, thus allowing real-time Classification of eggplant leaf diseases. Therefore, YOLOv8m is selected as the model that will be deployed within an in-house programmed system.

4. RESULTS AND ANALYSIS

Here, the experimental results and performance analysis of different configurations of the proposed YOLOv8-based eggplant leaf disease classification system are described. The accuracy of classification is measured by some standard classification metrics, including Accuracy, Precision, Recall, and F1 score for assessing the trained models. Comparison across various models' variants of YOLOv8 was also done to find the most suitable model configuration. After this, the training, prediction, and real-world performance are evaluated.

4.1. Training Accuracy Analysis

Figure 2 conveys the training accuracy curves of the YOLOv8 versions after the same number of training rounds. The approximate comparison of curves in the graph demonstrates the speed of classification performance improvement for each version of YOLOv8 during training. Each YOLOv8 version continuously increases classification performance after each round of training, and each version of YOLOv8 demonstrates the successful learning of deep features in the eggplant leaf dataset. YOLOv8n, the lightweight version of YOLOv8, has a slow convergence speed and a low classification accuracy. Meanwhile, larger versions of YOLOv8, such as YOLOv8m, have a stable convergence speed and a capacity for good classification performance. While YOLOv8l and YOLOv8x demonstrate a slightly higher classification achievement than other YOLOv8 versions, this comes at the cost of greater computational complexity and a longer training time than YOLOv8m. However, YOLOv8m achieves a better balance between performance and efficiency, which makes it more applicable in real-time disease classification applications. In this regard, the figure proves that the YOLOv8 architecture is suitable for Eggplant leaf disease classification and recommends that YOLOv8m is appropriate for implementation in real-world agricultural systems.

4.2. Training Loss Analysis

In Figure 3, we show how the training loss varies for different YOLOv8 model variants, YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x, over multiple epochs of training. The graph indicates how well each model minimizes the loss function for learning. All models have high loss in the initial epochs of training, and this reduces with each subsequent epoch. As a result, the decrease in loss suggests that both models are learning to reduce classification errors and improve their predictions over time. The last three YOLOv8m, YOLOv8l, and YOLOv8x models reach lower values of final loss compared to the original model, YOLOv8n, and remain faster in terms of loss reduction. The YOLOv8n model keeps relatively larger loss during training because it can not learn complex features from its lightweight architecture. Comparatively, larger models tend to have better optimization behavior because of their more powerful representational capabilities. YOLOv8m is the most efficient from the tradeoff perspective for convergence speed and computational cost, as the other large versions (YOLOv8l and YOLOv8x) are not, due to their very small differences in performance from YOLOv8m and their computational complexity. Overall, the training process is confirmed to perform the deep learning function of YOLOv8, which is to customize the training, and subsequently, the migration classification errors are minimized. Given the training results, YOLOv8m is the most effective model for the classification of eggplant leaf diseases.

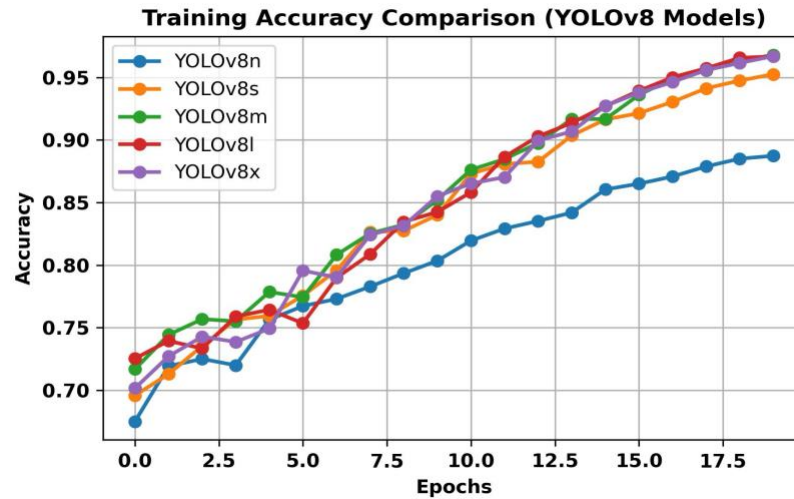


Figure 2. Training Accuracy for YOLOv8 Model

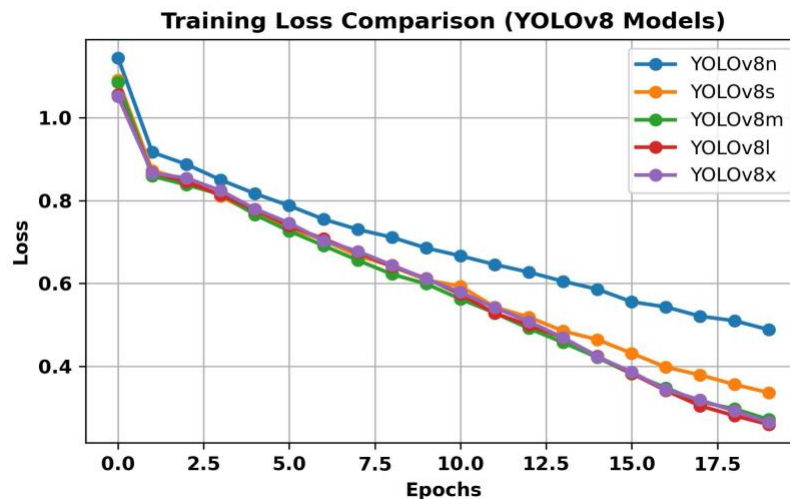


Figure 3. Training Loss for YOLOv8 Model

4.3. Confusion Matrix Analysis

Figure 4 provides the confusion matrices for YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x models for classifying eggplant leaf disease. A confusion matrix summarizes the results of a classification process by matching true class labels with predicted class labels. The statistics of the classification results for each confusion matrix are shown on the diagonal, and the statistics for the confusion cases among the disease classes are shown in the non-diagonal elements. Larger figures on the diagonal indicative of better classification performance and higher reliability or confidence in model predictions. The results indicate that all YOLOv8 variants perform well in terms of classification for most disease classes. Nevertheless, lightweight architectures such as YOLOv8n misclassify these diseases at a relatively higher rate than others, especially in a visually similar range of disease categories. This means low classification errors as the model complexity increases, good feature representation, and discrimination capability. Among the models evaluated, YOLOv8m shows highly consistent classification performance, and the misclassified samples in all disease categories are also much fewer compared to other models. From the confusion matrix of YOLOv8m, it is apparent that there is a dominant diagonal, suggesting that the healthy leaves were predicted correctly, and multiple disease conditions. While the YOLOv8l and YOLOv8x also perform competitively for classification, they require more computation than YOLOv8m. It also shows that diseases with distinct visual symptoms, such as Wilt Disease and White Mold Disease, are better classified in all

models. In classes that appear similar, Leaf Spot Disease and Mosaic Virus Disease, for example, there is minor confusion. Figure 4 verifies the effectiveness of the proposed YOLOv8-based classification framework and shows that both accuracy and stability are in harmony between classifying methods, with high classification efficiency to achieve real-time eggplant leaf disease identification, where YOLOv8m is a satisfactory one.

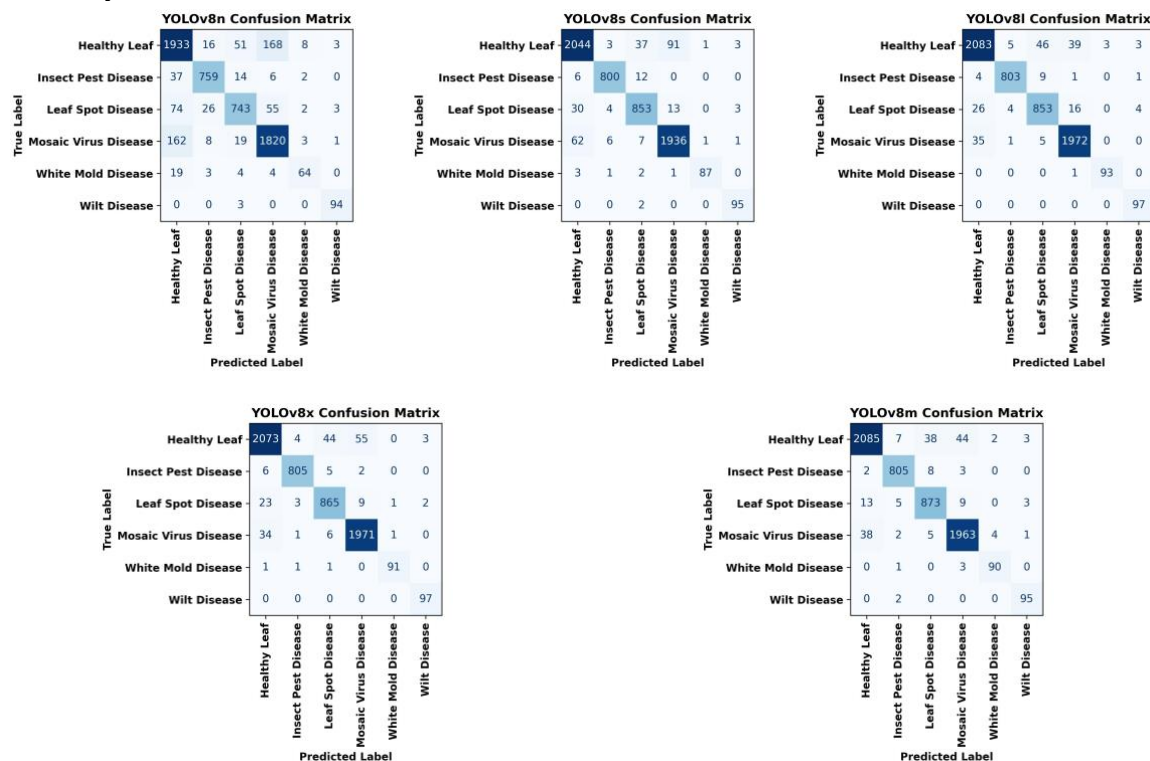


Figure 4. Confusion Matrix of Different YOLOv8 Models

4.4. ROC Curve Analysis

Figure 5 lays out the Receiver Operating Characteristic (ROC) curves for YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x versions for classifying eggplant leaf disease. The ROC curve observes the classification of the models by balancing the positive prediction rate with the false positive rate. All versions place the ROC curves for the disease models in the upper-left area, reflecting their deep understanding of the disease categories. All YOLOv8 models tested performed beyond a random guess classification. YOLOv8 models showed good predictions for separating different disease classes and good predictions relative to other classification models for this dataset. All variants of the YOLO v8 classification models showed the predicted class “leaf disease” trending toward the upper area of the curve. YOLOv8n models’ prediction class “leaf disease” trended toward being good, while YOLOv8m models’ curve, in addition to being good, showed a cutting prediction loss for class “leaf disease” in a leftward direction. YOLOv8m models showed the most class-stable ROC results for the evaluated class models, with the least computational implementation among the other evaluated models, YOLOv8l and YOLOv8x, respectively. All class disease prediction models remained with a good prediction, a class-stable and reliable model beyond a random prediction. The ROC analysis also highlights the parameter-set-built YOLOv8-based framework for the overall categorization capability of multiple eggplant leaf diseases. The results provide evidence that YOLOv8m is a practical candidate, balancing computational power demands and providing decent classification accuracy.

4.5. PR Curve Analysis

The Precision-Recall (PR) curves of eggplant leaf disease classification for YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x are illustrated in Figure 6. The PR curve quantifies the balance between precision and recall, thus providing a better assessment metric for classification reliability for each disease. The curves cluster in the upper right quadrant, indicating they are the best models for predicting a class and for discriminating between classes. The larger the curve area, the better the precision and recall. This means the models are classifying disease categories, and they are minimizing the model outputs that are

classified as positive when they are negative in reality, thus improving the quality of the disease recognition. The weaker PR characteristics of several classes in the YOLOv8n model could be attributed to the model not learning predictive features. This is in contrast to YOLOv8m, which exhibits precision-recall curves that are smooth and more stable on the boundaries, indicative of better variance in model prediction learning and classification. YOLOv8m curves are close to the optimal region, implying classification for healthy leaf samples remained stable, as did disease leaf classification. The high values of the area of the curves under the disease categories show that the classification model has a reliable Classification of the disease and recognition capability of the related patterns. On the other hand, the classes with the most visually similar symptoms exhibit less variance. The implementation of the YOLOv8-based system for multi-class eggplant leaf disease classification shows positive results. Both single and combined usage have shown results indicative of the system's capacity for practical real-time deployment, with YOLOv8m demonstrating more than adequate performance.

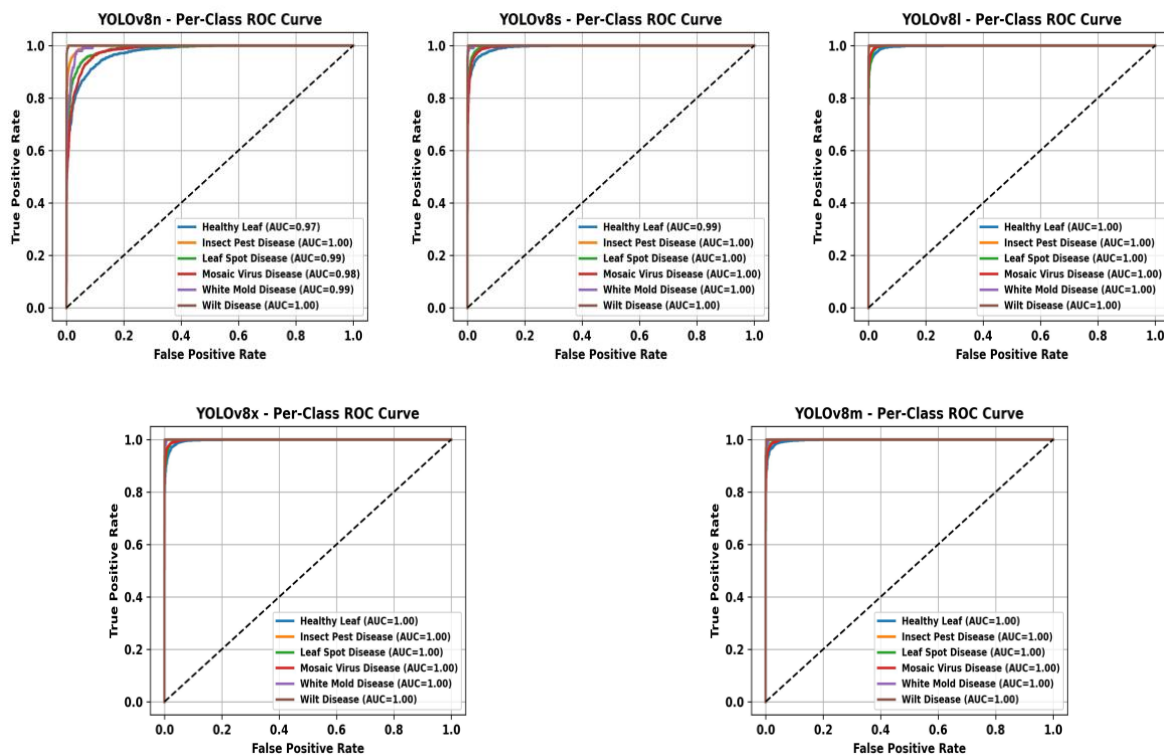
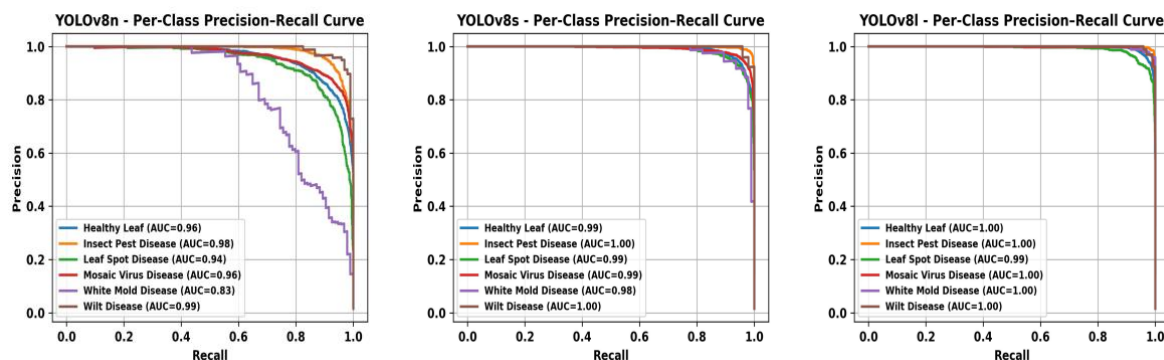


Figure 5. ROC Curve Comparison of YOLOv8 Models



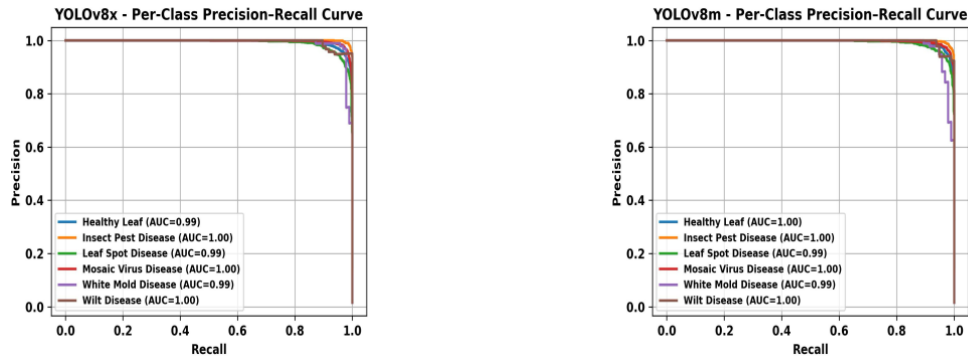


Figure 6. PR Curve Comparison of YOLOv8 Models

4.6. Performance Comparison Analysis

Performance metrics, including accuracy, precision, recall, and F1-score of the various YOLOv8-based architectures in the context of the classification of eggplant leaf diseases, are documented in Figure 7. The classification performance of the various designs has been summarized. YOLOv8n scored the lowest in performance compared to all architectures. From the comparative analysis of YOLOv8n, it can be inferred that its lightweight architecture was not able to learn disease-rich features. YOLOv8s, being of a larger design and compared to its predecessor, showed improved performance in classification. However, the performance compared to other larger variants was still scored lower because of YOLOv8s's comparatively weaker capacity in feature representation. YOLOv8l and YOLOv8x showed higher feature representation. In summary, these models have a higher potential to learn disease characteristics. However, each requires a substantial amount of RAM, inference time, and computational resources. Therefore, these models are less appropriate for real-time agriculture and other potential implementations that take place in resource-constrained circumstances. YOLOv8m scored the highest performance across all assessed architectures with an accuracy of 96.84%, a precision of 96.85%, a recall of 96.84%, and an F1-score of 96.84%. The result indicates that YOLOv8m can learn features of different diseases with the least variance in classification prediction. It also showed the least computational cost among larger models. In order to achieve real-time illness diagnosis in the field while also integrating the tracking system for targeted disease diagnosis, a precise agriculture system is essential. The YOLOv8m exhibits excellent performance in the real-time classification of eggplant leaf diseases.

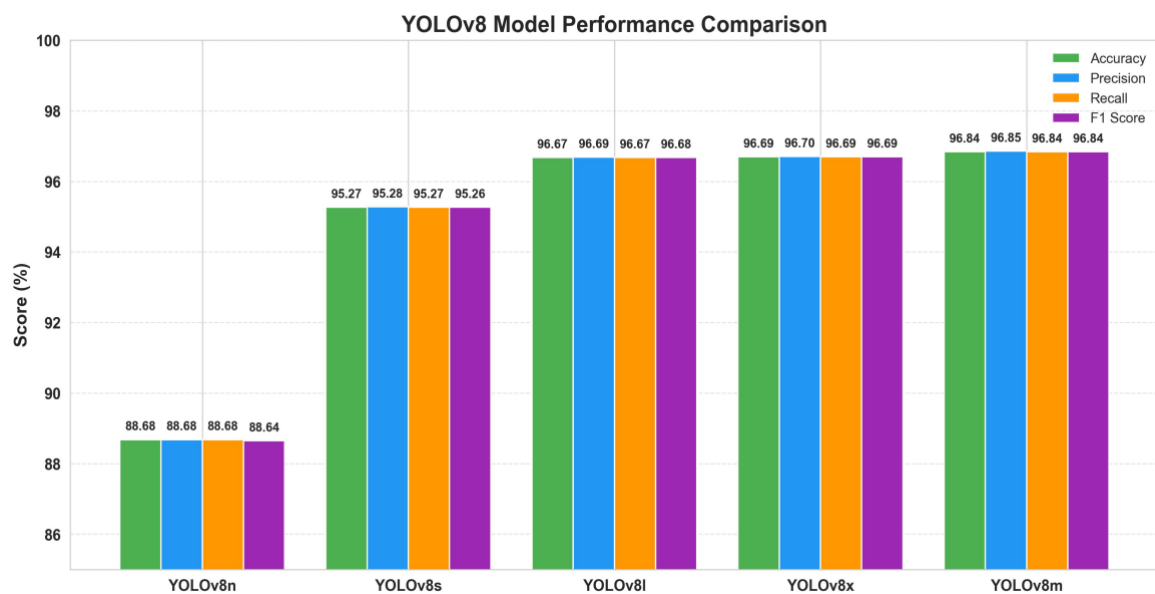


Figure 7. Evaluation Metrics Performance Comparison of Multiple YOLOv8 Models

4.7. Model Interpretability Analysis

The proposed YOLOv8m Framework for Eggplant Leaf Disease Classification shows visual results for interpreting the framework using Grad-CAM, Grad-CAM++, and EigenCAM, as shown in Figure 8. Since YOLOv8m is based on the architecture of the YOLO (You Only Look Once) framework, the results show how the trained model identifies parts of the image and is likely to focus and concentrate on classification. The first row is the original input images, which are classified as healthy leaf, white mold disease, leaf spot disease, wilt disease, mosaic virus disease, and insect pest disease, in that order. The following rows show various interpretations using the trained model, which determines model classification. The white mold and mosaic virus disease samples show regions of the image that are possibly infected and discolored, and are likely to focus on disease symptoms. The Grad-CAM and Grad-CAM++ techniques focus strictly on disease symptoms, and EigenCAM tends to represent a larger area in the image. The examples show consistency in identifying disease features in the provided dataset. The visual attention analysis shows the YOLOv8m architecture's ability to highlight the ease and flexibility of the approach in locating disease symptoms. This enhances the thoroughness of the deep learning process and builds a consistent classification model appropriate for real-world applications in farming. The YOLOv8m-based framework can capture specific visual disease patterns and provide a fully understandable decision-making process for the classification of eggplant leaf disease.

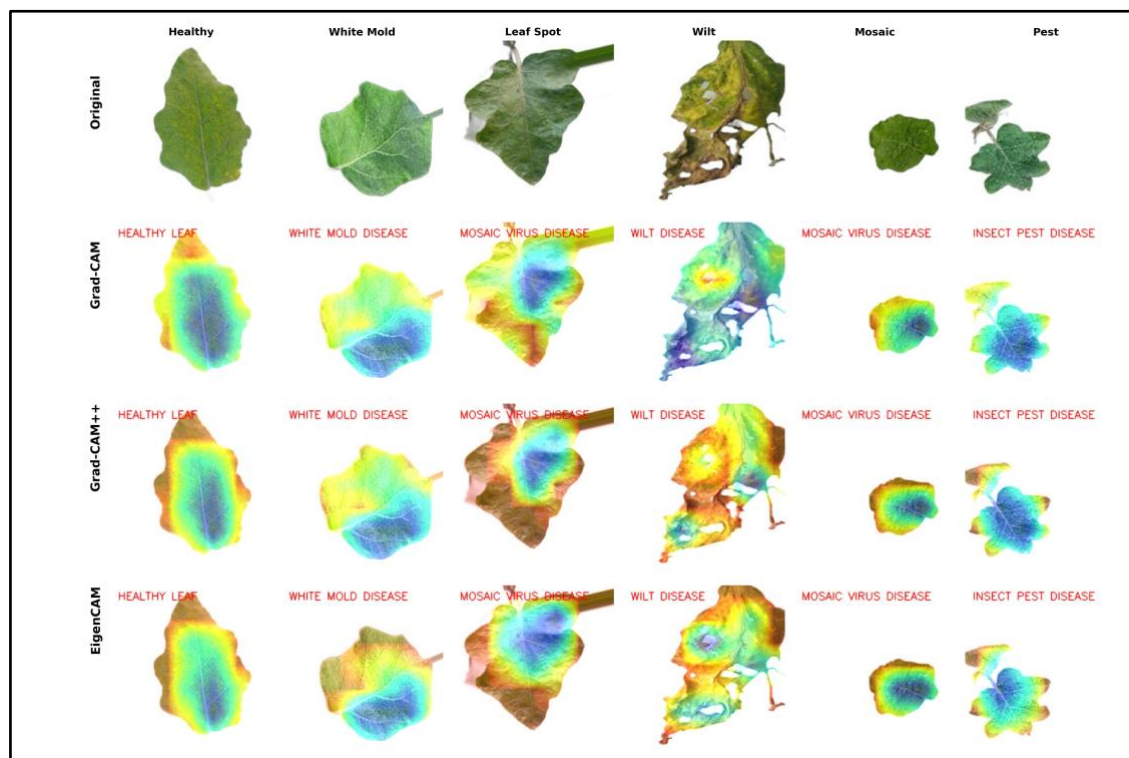


Figure 8. Eggplant Leaf Disease Classification YOLOv8m Visualization

4.8. Application Interface and Prediction Results

Figure 9 depicts a tree-based CV in a real-time eggplant leaf disease classification application using a YOLOv8m-based web application. Leaf images were uploaded, and responses were provided in real-time regarding disease prediction using the interactive interface. This app performed a multi-class classification on various disease classes: Healthy Leaf, White Mold Disease, Leaf Spot Disease, Wilt Disease, Mosaic Virus Disease, and Insect Disease. Each of the uploaded images was provided with a classification and confidence score, affirming the reliable prediction of various disease conditions. The interface employed Grad-CAM, Grad-CAM++, and EigenCAM visualization methods for interpretability. These heatmap visualizations highlight the most influential image regions for the classification. This shows the symptoms of the disease spread over the classification leaf. Introducing the used activation maps, we can conclude that our model focuses on almost all lesion areas, patches of discoloration, infected textures, and the structure of damaged leaves for different diseases. This visualization plays an important role in validating the learning behavior of the proposed framework, as well as enabling a clear insight into the prediction analysis. The deployment

results confirm real-time leaf processing from previously unseen instances of the high-resolution image sets classified with stable performance using the YOLOv8m model. Streamlit's interface, being light and easy to use, further enhances the experience of using it practically in the field for agricultural monitoring applications. The applications of this framework include automated eggplant leaf disease Classification and a real-time precision agriculture support system.

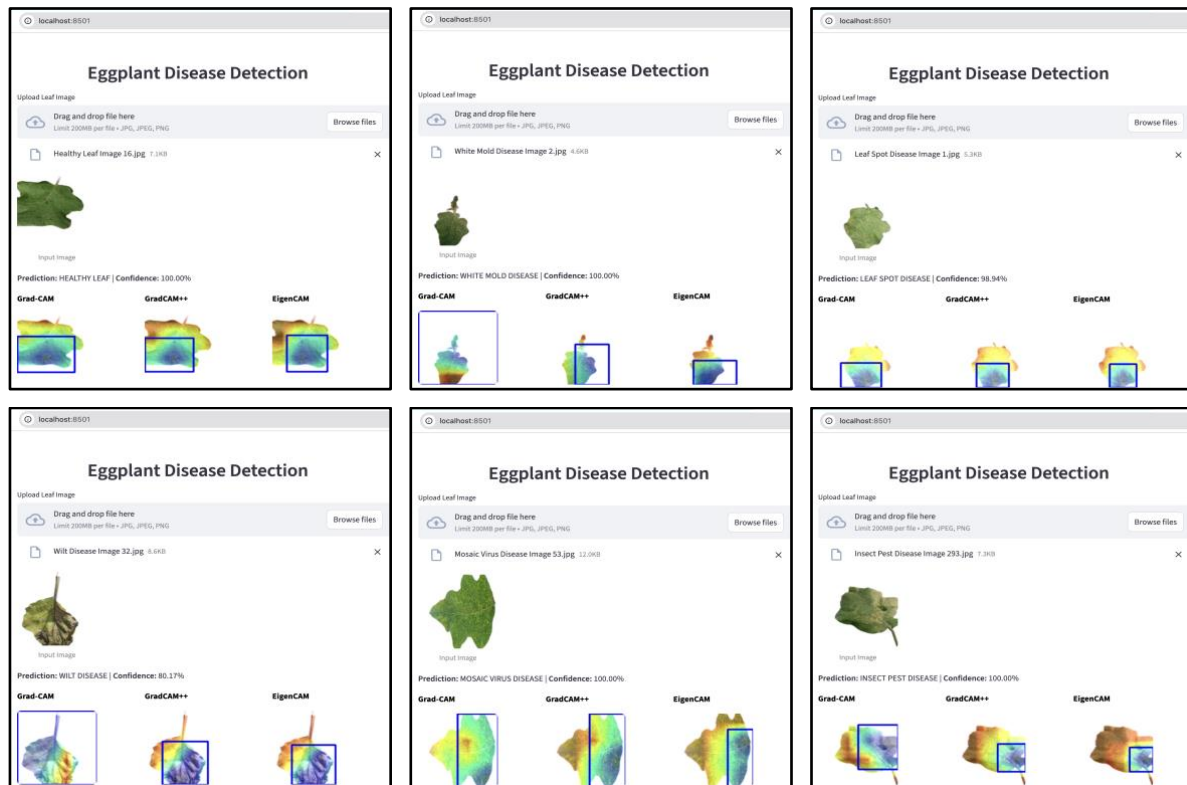


Figure 9. Real-Time Classification Interface of Eggplant Leaf Diseases Using Streamlit

5. CONCLUSION

In this study, an eggplant leaf disease classification framework was proposed through automated methods based on YOLOv8 deep learning models and a custom multi-class dataset including the categories of Healthy Leaf, White Mold Disease, Leaf Spot Disease, Wilt Disease, Mosaic Virus Disease, and Insect Pest Disease. Image preprocessing and augmentation techniques were performed to ensure diversity of features and improve classification robustness. YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x architectures were used for experimental evaluation. YOLOv8m outperformed the other variants with an overall accuracy of 96.84%, a precision of 96.85%, a recall of 96.84%, and an F1-score of 96.84%. Thus, this model could be a robust disease classification model with better convergence and lower classification error among most of the disease classes. The confusion matrix, ROC curves, and Precision–Recall analysis all supported the ability of the YOLOv8m architecture to distinguish visually similar disease patterns while providing reliably accurate predictive performance. Grad-CAM, Grad-CAM++, and EigenCAM were performed to verify whether the model correctly focused on the infected region and relevant features during prediction. In addition to this, a web-based application using the Streamlit framework is constructed that contains capabilities for real-time uploading of images and generating predictions with confidence estimates, in addition to visualizing the interpretation of classification results. The deployment results showed that the framework we proposed was practical for precision agriculture and automated crop monitoring applications. The proposed YOLOv8m-based system has generally been shown to be standard, fast, efficient, and explainable for eggplant leaf disease classification against traditional approaches and contributes to timely disease management in precision agriculture environments. Future work will target the capture of large-scale field-level datasets, optimize lightweight deployment strategies, and incorporate mobile or IoT-enabled platforms for real-time smart farming applications.

DATA AVAILABILITY STATEMENT

The original data presented in the study are openly available in Mendeley Data "Eggplant Leaf Disease Prediction Dataset", at doi: 10.17632/d3ypkphghb.2

CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest.

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Osamah Ibrahim Khalaf, professor at Al-Nahrain University. I have a strong research background in computer science and information technology, 17 years of university-level teaching experience, over 141 ISI-indexed publications, and numerous international conference presentations. I hold two Australian patents, have completed over 1300 peer reviews, and have received multiple awards for my innovative work. I also have an h-index of 61. I am a highly accomplished researcher and academic with a strong international reputation due to my contributions to computer science. My work has been widely acknowledged through prestigious awards, patents, publications, and leadership roles in global academic and research communities, including committee and editorial roles for international conferences and journals. Throughout my career, I have contributed to critical advancements in embedded and Real-Time Communication Systems, wireless sensor networks, and healthcare security. My work on a water resource management system for a sustainable environment (400+ citations) has optimized urban water use through smart systems and green infrastructure. In energy-efficient clustering for wireless sensor networks (500+ citations), I developed algorithms to extend network lifespan and enhance performance for applications like environmental monitoring and smart agriculture. Additionally, my research on secure healthcare systems using machine learning (200+ citations) leverages AI-driven approaches, such as support vector machines, to protect medical data and improve patient trust. These accomplishments not only demonstrate the impact of my research across multiple disciplines but also underscore my ability to drive continued innovation in the World, contributing to advancements in sustainability, technology, and public health. In the coming years, I intend to extend my research to develop more efficient, interpretable, Embedded and Real-Time Communication Systems and ethical AI models, including federated learning, generative AI (e.g., large language models and diffusion models), AI for scientific discovery, quantum machine learning, error correction, and hybrid quantum-classical systems. A major challenge in the field is improving the robustness and fairness of AI systems, particularly in high-stakes decision-making areas such as healthcare, criminal justice, and hiring. My research aims to develop methods to audit and mitigate biases in datasets and models while maintaining performance, design interpretable AI architectures without sacrificing accuracy, and enhance adversarial robustness through novel training paradigms or formal verification. My work aligns with the growing demand for ethical, trustworthy AI in the World where regulatory frameworks and industry needs are rapidly evolving. This research is highly relevant to the World which invests heavily in quantum technologies, as breakthroughs have revolutionary implications for optimization, cryptography, and materials science. He can be contacted at email: usama81818@nahrainuniv.edu.iq.