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A YOLO and CNN based Approach to Detect and Classify Diseases in Apple Plant Leaves

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***Abstract*— The agricultural sector plays a pivotal role in sustaining human civilization, with plant diseases having a substantial impact on both crop yield and quality. Early and accurate detection of plant diseases is essential for effective disease management and precision agriculture. In this study, a CNN-based approach for detecting deformities in plant leaves, using deep learning models including YOLO v8 for region of interest (ROI) extraction and VGG16, ResNet50, and InceptionV3, for image classification trained on the Plant Village dataset for the diseases scab, rot, and rust in apples along with healthy leaves has been proposed. The accuracy of the proposed approach was evaluated, and a graphical user interface (GUI) was developed for convenient disease detection. The ResNet50, VGG16, and InceptionV3 models achieved validation accuracy of 64%, 94%, and 96% respectively.**

***Index Terms*— CNN, deep learning, YOLO v8, VGG16, ResNet50, InceptionV3, Plant Village dataset.**

I. INTRODUCTION

Agriculture stands as the cornerstone of numerous economies worldwide, playing an indispensable role in sustaining food security and economic stability. However, this crucial sector faces a formidable adversary in the form of plant diseases, which threaten crop production. The timely detection of these diseases is imperative to curtail their spread and minimize the resulting agricultural losses. Traditional methods of disease identification primarily rely on the visual acumen of trained experts, a process that can prove labor-intensive, subject to interpretation, and impractical for extensive farming operations. In recent years, a burgeoning interest has emerged in harnessing the potential of image processing and machine learning techniques to forge automated and precise plant disease detection systems tailored for the realm of precision agriculture. This paradigm shift has the potential to revolutionize how agriculture is practiced, offering farmers innovative tools to address the age-old challenge of plant diseases effectively. For India, agriculture holds a paramount position, serving as a linchpin of the nation's economy and providing sustenance to a substantial proportion of its populace. The country boasts a rich agricultural heritage, characterized by a diverse array of crops cultivated across varying climatic zones. As per the Ministry of Agriculture and Farmers Welfare, Government of India, this sector contributes approximately 18% to India's Gross Domestic Product (GDP) and employs nearly half of the workforce. Yet, the Indian agricultural landscape contends with a spectrum of challenges, encompassing climate vagaries, pest infestations, insufficient infrastructure, limited access to modern agricultural methodologies, and lackluster productivity. Among these challenges, the scourge of crop diseases looms prominently, precipitating substantial agricultural losses, diminished yields, and economic hardships for farmers.

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A sobering report by the National Sample Survey Office (NSSO) in 2019 on the "Agricultural Situation in India" reveals a concerning uptrend in the prevalence of crop diseases within the country. A litany of afflictions, including rust, blight, wilt, and rot, has afflicted a pantheon of crops, spanning rice, wheat, cotton, vegetables, and fruits. The ripple effects of these diseases cascade through the agricultural ecosystem, imperiling farmers' livelihoods, food security, and the broader economy.

In this context, the integration of advanced image processing and deep learning techniques for the early detection of diseases in plant leaves emerges as a beacon of hope for revolutionizing precision agriculture practices in India. The accurate and prompt identification of plant diseases through these cutting-edge technologies equips farmers with the knowledge and tools needed to staunch the spread of diseases and ameliorate their deleterious effects on crop production. By embracing these modern methodologies, farmers can make informed decisions, optimize resource allocation, and embrace sustainable farming practices, ultimately leading to enhanced agricultural productivity and improved livelihoods.

This study stands out by addressing critical challenges in plant disease detection methodologies. We aim to enhance the reliability of deep learning models for this task, particularly focusing on potential biases within the widely used datasets. The methodology proposed here pioneers' approaches to mitigate these biases, contributing to the development of more accurate and unbiased plant disease detection models. By tackling these challenges head-on, our work is positioned to make a significant impact on the effectiveness of agricultural practices and crop management. The aim of the study is to draw a comparison of the different standardized frameworks and to provide insights into the practical implications of employing various deep learning models for disease detection in plant leaves.

II. Literature Review

In recent times, there has been a surge in the use of deep learning algorithms for the identification of plant leaf diseases, attracting considerable attention from researchers. Numerous investigations have been carried out to assess the efficacy of different deep learning models within this field. Juncheng Ma et al.'s [1] exploration of deep convolutional neural networks (DCNN) for cucumber disease recognition provides a pertinent foundation for the study. Demonstrating a robust 93.4% accuracy, their work showcases the effectiveness of DCNN in segmenting and recognizing symptoms from field-captured leaf images. As we delve into implementing a YOLO and CNN-based approach for disease detection in apple plant leaves, this study serves as a benchmark, emphasizing the viability of deep learning methodologies for accurate and efficient disease classification in plant leaves. Dengshan Li et al.'s [2] study introduces a custom backbone deep learning video detection system for rice plant diseases and pests. The method, using faster-RCNN, transforms videos into still frames and outperforms VGG16, ResNet-50, ResNet-101, and YOLO v3 in detecting untrained rice videos. The inclusion of video-based evaluation metrics enhances the quality assessment. This research informs the study by providing insights into effective video-based disease and pest detection systems, particularly relevant to the exploration of a YOLO and CNN-based approach for apple plant leaf disease detection. Singh et al.'s [3] review delves into the urgent need for effective plant disease detection in agriculture. Recognizing the global impact of diseases on crop production, the authors emphasize the devastating effects, particularly for small-scale farmers. The paper focuses on the latest trends and challenges in using imaging techniques and computer vision for plant disease identification and classification. This review informs the study by providing valuable insights into evolving methods for disease detection.

The study specifically focused on the apple leaf classes within the dataset curated by Arun Pandian J and Geetharamani Gopal [4]. While the dataset comprises 39 classes covering various plant diseases and healthy states, the research narrowed its scope to leverage the images associated with apple leaves. Andreas Kamilaris and Francesc X. Prenafeta-Boldú [5] conduct a survey on the application of deep learning in agriculture, focusing on image processing and data analysis. Examining 40 research efforts, the survey delves into diverse agricultural challenges. The authors assess specific models (including ResNet, VGG16, and InceptionV3), data sources, preprocessing techniques, and performance metrics. Their findings highlight the superiority of deep learning over traditional image processing methods, consistently delivering high accuracy in various agricultural contexts. This survey contributes valuable insights to the study, complementing the use of ResNet, VGG16, and InceptionV3 models in the context of apple plant leaf disease detection. Konstantinos Ferentinos [6] introduces a paper focusing on the development of convolutional neural network (CNN) models for plant disease detection and diagnosis using leaf images. The models were trained on an extensive database of 87,848 images encompassing 25 different plants in 58 distinct [plant, disease] combinations, including healthy plants. The best-performing model achieved an impressive 99.53% success rate in identifying the corresponding [plant, disease] combination or healthy plant. This exceptional accuracy positions the model as a valuable advisory and early warning tool, suggesting its potential for integration into a real-time plant disease identification system. Ferentinos's work aligns with the study, utilizing deep learning models (including CNNs) for disease detection in apple plant leaves, and provides insights into the high success rates achievable in similar contexts.

Jayme G. A. Barbedo's [7] article delves into the application of deep learning for plant disease recognition, emphasizing the need to consider factors that affect the design and effectiveness of deep neural nets in plant pathology. Through an in-depth analysis, Barbedo highlights both advantages and shortcomings, drawing on studies from the literature and experiments conducted with a generously shared image database containing almost 50,000 images. This critical examination emphasizing the importance of understanding the nuanced factors influencing their application. Lili Li, Shujuan Zhang, and Bin Wang's [8] 2021 review explores the application of deep learning in plant disease detection. Emphasizing the advantages of automatic learning, the review addresses the objective feature extraction in plant disease recognition, enhancing research efficiency. It provides an overview of recent progress, current trends, and challenges in deep learning technology for crop leaf disease identification. This concise review aligns with the study, offering insights into the advancements and challenges in utilizing deep learning for disease detection in apple plant leaves. Jun Liu and Xuewei Wang's [9] review focuses on plant diseases and pests' detection using deep learning, emphasizing the technology's superiority over traditional methods in digital image processing. The study categorizes recent research into classification, detection, and segmentation networks, summarizing their advantages and disadvantages. Common datasets and study performances are compared, addressing challenges and proposing solutions for practical applications of deep learning in this context. Lawrence C. Ngugi, Moataz Abelwahab, and Mohammed Abo-Zahhad [10] provide a comprehensive review on recent image processing techniques for automated leaf pest and disease recognition. The paper emphasizes the shift towards deep learning for crop pest and disease recognition, particularly using RGB images due to their low cost and high availability. The review discusses the performance of ten CNN architectures, highlighting recognition accuracy, recall, precision, specificity, F1-score, training duration, and storage requirements. Recommendations for suitable architectures in various computing environments are provided, along with discussions on unresolved challenges for developing practical automatic plant disease recognition systems in field conditions. Chai Ali, Li Baoju, et al. [11], present a study on tomato foliage disease recognition using computer vision technology. The research employs image processing and pattern recognition to detect diseases in tomato leaves. The study extracts color, texture, and shape characteristics, achieving high classification accuracies, such as 100% for the training set and 94.71% for the testing set using discriminant analysis. The model based on principal component analysis reaches a classification accuracy of 98.32%. This preliminary study indicates the feasibility of using computer vision for identifying and classifying tomato diseases, with potential for future online field applications. This aligns with the study on disease detection in apple plant leaves, offering insights into computer vision and image processing applications.

Yohannes Agegnehu Bezabh et al. [13] proposed a hybrid method for classifying pumpkin diseases, leveraging features extracted from ResNet and LeNet networks. Their research achieved notable accuracy rates, demonstrating the efficacy of the hybrid CNN ResLeNet model in identifying pumpkin leaf and fruit diseases from digital images. This approach aligns with our study's focus on utilizing deep learning techniques, such as convolutional neural networks (CNNs), for disease detection in plant leaves. While our investigation targets apple plant leaves specifically, the methodology and findings of Bezabh et al. [13] underscore the broader applicability of deep learning methodologies across diverse plant species, enriching our understanding of disease classification methodologies. Similarly, G. C. Wakchaure et al. [14] introduced an image processing-based maturity detection prototype device for classifying custard apple fruit based on various physical, chemical, and imaging features. Their utilization of machine learning algorithms, such as K-means clustering and SVM, resulted in a remarkable 100% accuracy in grading custard apple fruit at different maturity stages.

Mehmet Alican Noyan's [12] investigation into bias within the PlantVillage dataset highlights potential challenges in using the dataset for training deep learning-based plant disease detection models. The study revealed that a model trained with minimal information achieved an accuracy of 49.0%, indicating the presence of noise correlated with the labels. As we utilize the PlantVillage dataset in the study, it's essential to be mindful of potential biases and consider the implications for the model training and evaluation processes.

This extensive literature survey demonstrates the growing interest in applying deep learning techniques to plant disease detection and related applications, yielding promising outcomes and ongoing efforts aimed at enhancing accuracy and efficiency. Nevertheless, there remain opportunities for further research to address specific limitations and explore novel areas of application. Building upon the existing literature, the research proposes a comprehensive study that addresses critical challenges in plant disease detection, leveraging insights gained from the reviewed literature to pioneer advancements in the field.

III. METHODOLOGY

Plants are susceptible to various deformities in their leaves due to genetic mutations, environmental stressors, and disease infections. Early detection of leaf deformities can aid in identifying the underlying causes and taking appropriate actions to mitigate potential damage. Image processing and machine learning techniques can provide a non-invasive and efficient way to detect leaf deformities from images of plant leaves.

The methodology involves using the Plant Village dataset, focusing on apple leaf disease classification. YOLO v8 is employed for precise disease area detection through custom bounding box annotations. Extracted Region of Interest (ROIs) from the diseased areas are passed through pre-trained models, VGG16, ResNet50, and InceptionV3, to extract high-level features. Subsequently, separate classifiers are trained for each model using these features and corresponding disease labels. Evaluation metrics such as accuracy, precision and recall assess model performance. Fig. 1 represents a Graphical Abstract for the methodology of the study that gives a high-level understanding of the system.

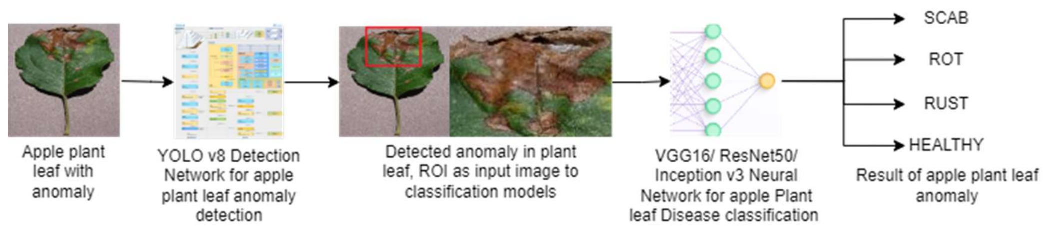

Figure 1. Graphical Abstract for the system.

A. Dataset

The study uses the Plant Village dataset [4] that is a widely used dataset in the field of plant pathology for developing and evaluating plant disease detection algorithms. It consists of a large collection of labeled images of healthy and diseased plant leaves. The dataset covers a wide range of crop species and includes various types of plant diseases. In this dataset, 39 different classes of plant leaf and background images are available. The dataset containing 61,486 images. The research primarily centers around four categories of apple Leaves: Rust, Rot, Scab, and Healthy. Specifically, the apple Scab, apple Black Rot, cedar apple Rust, and Healthy apple leaf classes have 630, 621, 276 and 1645 images, respectively. Fig. 2 highlights the dataset classes and visually represents few samples from each class.

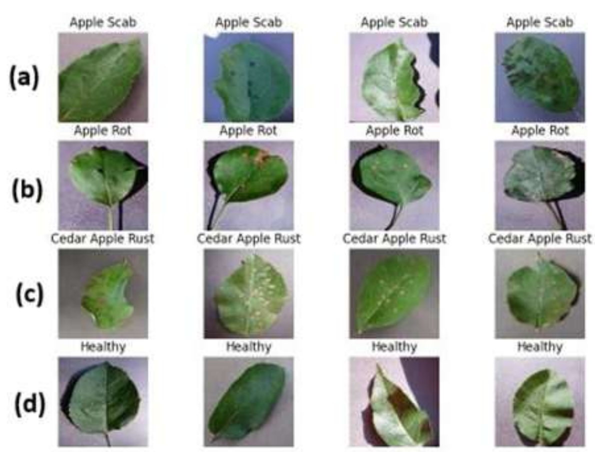

Figure 2. Plant Village dataset (a) scab, (b) rot, (c) rust, and (d) healthy

B. Extraction of ROI using YOLO v8

The present research employs YOLO v8, a state-of-the-art object detection model developed by ultralytics, to identify leaf spots or anomalies. The model was trained on the plant village dataset to precisely delineate the ROI. The yolov8m.pt variant of the model has been utilized as the base model for its balance between accuracy and frames per second (FPS) performance.

Utilizing the bounding box coordinates generated by YOLO v8, a new dataset containing the extracted ROIs was created. These extracted images were then organized based on their corresponding classes and subsequently utilized in conjunction with CNNs for further processing and analysis.

For training the model, a subset of the dataset was used, consisting of 29 images from each class, annotated with bounding boxes to mark anomalies present on the leaf surface. Roboflow annotator was used to label and prepare the dataset. Fig. 3 provides a detailed insight into the dataset preparation and training process employed for the YOLO v8 Deep Neural Network. This figure outlines the crucial steps involved in data collection, preprocessing, and the subsequent training of the YOLO v8 model.

In scenarios where the YOLO v8 detection model produces inaccurate predictions, leading to potential misclassification of anomalies in plant leaves, a systematic corrective action is implemented. Specifically, if the YOLO v8 model generates incorrect predictions, the class designation assigned to the corresponding ROI is labeled as "Healthy." This intentional labeling of inaccurately detected ROIs as "Healthy" is a deliberate measure aimed at preventing false positives from influencing subsequent stages of the disease detection pipeline. By classifying misidentified regions as healthy, we ensure that only the reliable and accurate anomalies proceed through the subsequent layers of our methodology. This approach is pivotal in maintaining the integrity of the disease classification process, as it prevents the propagation of erroneous information and contributes to the overall precision and reliability of the detection system.

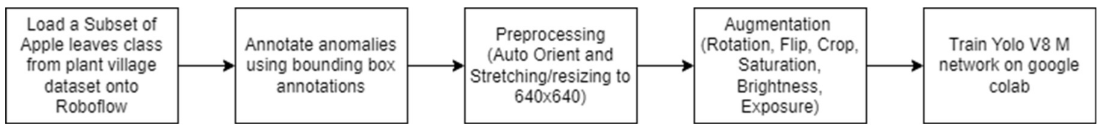

Figure 3. Dataset Preparation and training process for YOLO v8 Deep Neural Network. (ROI Dataset preparation).

C. Preprocessing and Augmentation

Before commencing YOLO v8 training, a series of preprocessing steps and augmentations were executed to enhance the dataset's size and introduce diversity. The algorithm, named Image Preprocessing, took a set of training examples containing images as input and generated pre-processed training examples with augmented images as output. The process involved several key steps: auto-orienting each image, resizing them to 640x640 pixels, and creating three augmented versions for each image. These variations included horizontal and vertical flips, 90° rotations (clockwise, counter-clockwise, upside down), random cropping with zoom levels ranging from 0% to 25%, and adjustments in saturation, brightness, and exposure within the range of -25% to +25%. The original image, along with its three augmented versions, was included in the final set of pre-processed training examples.

D. Deep Learning Models

We utilized three popular deep learning architectures, namely VGG16, ResNet50, and InceptionV3, to train the plant disease detection model.

Visual Geometry Group 16 (VGG16)

VGG16 is a convolutional neural network consisting of 16 weight layers, including 13 convolutional layers and 3 fully connected layers. It uses small 3x3 convolutional filters with a stride of 1 and employs max-pooling layers for down sampling. VGG16 comprises multiple convolutional blocks, each with a set of convolutional layers followed by max-pooling layers. The convolutional layers extract hierarchical features, and max-pooling reduces spatial dimensions. The fully connected layers at the end perform classification. The core operations in VGG16 involve convolution, ReLU activation, and max-pooling:

$$\text{Convolution Output} = \text{Activation}\ (\text{Convolution}\ (\text{Input, Filters}) + \text{Bias}) \ldots (1)$$

where "Activation" is typically a Rectified Linear Unit (ReLU) function.

$$\text{Max-Pooling Output} = \text{Max}(\text{Input, Pooling\_Size}) \ldots (2)$$

Residual Network (ResNet50)

ResNet50 is a deep residual network with 50 weight layers. It introduces residual connections, or skip connections, which help alleviate the vanishing gradient problem and enable training of very deep networks. ResNet50 consists of multiple residual blocks, each containing convolutional layers and shortcut connections. The shortcut connections bypass one or more convolutional layers. The key equation in ResNet50 is the residual block:

$$\text{Output} = F(\text{Input}) + \text{Input} \ldots (3)$$

where "F" is the transformation applied by the layers in the block.

GoogLeNet (InceptionV3)

InceptionV3 is known for its inception modules, which use multiple filter sizes in parallel to capture features at different scales. It has a total of 48 layers. InceptionV3's architecture is characterized using multiple inception modules, which consist of parallel convolutional and pooling operations with different filter sizes. These modules are concatenated to form the network. The key operation in Inception modules is concatenation:

$$\text{Output} = \text{Concatenate}(\text{Conv1x1}, \text{Conv3x3}, \text{Conv5x5}, \text{Max-Pooling}) \quad \dots (4)$$

where different filters (1x1, 3x3, 5x5) are applied in parallel to the input, and their results are concatenated.

E. Model Training and Evaluation

The deep learning models were trained using a train-validation split approach, with 75% of the data used for training, 12.5% for validation and 12.5% dataset was reserved for testing purposes. While test-train-val split, all classes were individually divided to ensure accurate evaluation and training. The training was performed using a batch size of 32, and the models were trained for 10 epochs on a tesla T4 GPU available freely on Google Colab. Fig. 4 presents a high-level overview of the training and evaluation processes for all Deep Neural Networks (DNNs) used in the study. This figure offers a comprehensive view of the workflow, from data acquisition to model assessment, highlighting the common elements and stages across different neural network architectures. (Note that the data given as an input to these models is obtained after extracting the ROI using YOLO v8).

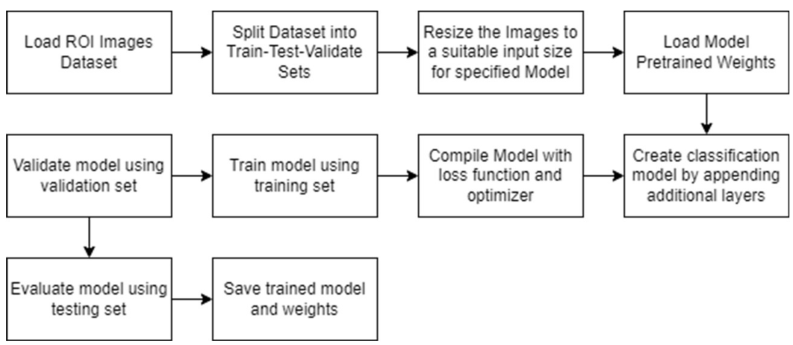

Figure 4. Dataset Preparation and training process for VGG16, ResNet50 and InceptionV3 Deep Neural Networks

F. Graphical User Interface (GUI)

To make the disease detection process more user-friendly and accessible, a Graphical User Interface (GUI) for the model has been developed. The GUI allows users to select an image of a plant leaf from their local system, and then choose the desired deep learning model from the three models namely VGG16, ResNet50, or InceptionV3 for disease detection. The selected model processes the input image and provides the output prediction, indicating whether the leaf is healthy or infected with scab, rot, or rust disease. Fig. 5 showcases snapshots of the Graphical User Interface (GUI) developed for the plant leaf disease detection application. These images offer a glimpse into the user-friendly interface that allows users to interact with the system, input images, and view the results effortlessly.

Figure 5. Snapshots of GUI for plant leaf disease detection

IV. RESULTS

The proposed approach using VGG16, ResNet50, and InceptionV3 architectures achieved high accuracy in detecting the diseases scab, rot, and rust in apples along with healthy leaves. The VGG16, ResNet50, and InceptionV3 models achieved validation accuracies of 94%, 64%, and 96%, respectively, on the validation set. These results demonstrate the effectiveness of the deep learning models in detecting plant diseases paired with preprocessing and ROI extraction with YOLO v8.

The results for detecting spots on leaf are denoted in Table 1, the "Class" column lists the disease classes being considered, which include "all" (all diseases combined), "rot," "rust," and "scab". The column "Images" indicates the total number of images in the dataset for each disease class. "Instances" column represents the total number of disease instances (leaf samples with diseases) within each class. Column "Box(P)" corresponds to Precision, "R" corresponds to Recall, "mAP50" corresponds to Mean Average Precision at IoU threshold 0.50, and "mAP50-95" corresponds to Mean Average Precision calculated over IoU thresholds from 0.50 to 0.95.

A. Box(P) (Precision of bounding boxes)

Box(P) measures how accurately the model localizes objects within bounding boxes. It is crucial in object detection tasks, ensuring that the predicted bounding boxes closely match the ground truth boxes. Box(P) is calculated as the number of correctly predicted bounding boxes (True Positives or TP) divided by the total number of predicted bounding boxes (TP + False Positives or FP).

$$Box(P)=TP/((TP+FP)) \dots (5)$$

B. R (Recall)

Recall measures how effectively the model identifies all relevant instances of an object class in the dataset. High recall means that the model rarely misses instances of the object class. Recall is calculated as the number of correctly predicted instances (True Positives or TP) divided by the total number of actual instances of the object class (TP + False Negatives or FN).

$$R=TP/((TP+FN)) \dots (6)$$

C. mAP50 (Mean Average Precision at 50)

mAP50 is a common metric in object detection that measures the overall accuracy of the model. It evaluates how well the model ranks and identifies objects within the top 50% of its predictions. To calculate mAP50, you first compute the Average Precision (AP) for each class, and then take the mean of these AP values across all classes. The AP for a class is determined based on precision and recall values at different confidence thresholds.

D. mAP50-95 (Mean Average Precision from 50 to 95)

mAP50-95 is a metric used in object detection that assesses the overall accuracy of a model across different Intersection over Union (IoU) thresholds, ranging from 0.5 to 0.95. Unlike mAP50, which focuses on precision and recall at a fixed confidence threshold, mAP50-95 considers a broader spectrum of IoU values. The metric calculates the Average Precision (AP) for each class at IoU thresholds from 0.5 to 0.95 and then computes the mean of these AP values across all classes. This provides a more comprehensive evaluation of a model's performance across a range of IoU criteria.

TABLE I. RESULTS OBTAINED AFTER TRAINING YOLO V8-M ON CUSTOMIZED DATASET.

Class	Images	Instances	Box(P)	R	mAP50	mAP50-95
all	29	139	0.633	0.578	0.562	0.257
rot	29	25	0.820	0.909	0.861	0.467
rust	29	50	0.546	0.560	0.467	0.176
scab	29	64	0.534	0.266	0.356	0.128

Fig. 6 presents the training results for the YOLO v8 model, which encompasses multiple training result graphs. The horizontal axis represents the number of training epochs, tracking the progression over time, while the vertical axis indicates the loss values. These loss values comprise "box_loss," measuring bounding box accuracy; "cls_loss," gauging classification performance; and "dfl_loss," assessing deformable convolution handling. Lower loss values signify improved model performance. The combined insights from these graphs help evaluate the model's learning and convergence throughout the training process.

Fig. 7 focuses on the ROI detection capabilities of the YOLO v8 model. It visually demonstrates how the model identifies and highlights specific regions within an image that are relevant to plant leaf disease detection, aiding in precise analysis.

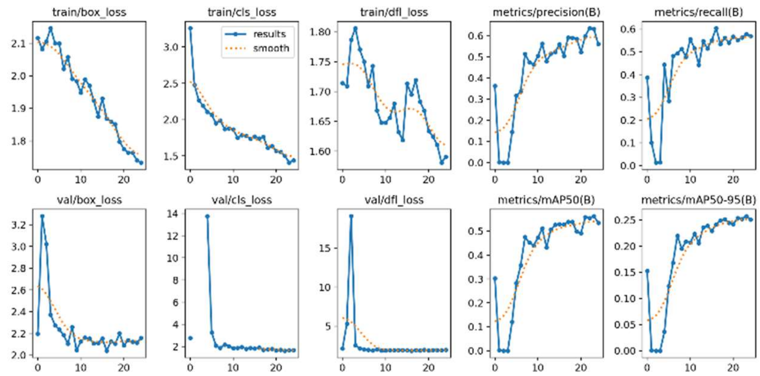

Figure 6. Training results for YOLO v8 detection

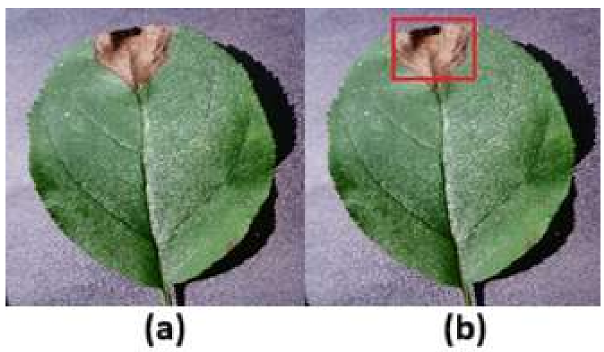

Figure 7. (a) Test image, (b) ROI extraction from leaf disease detection

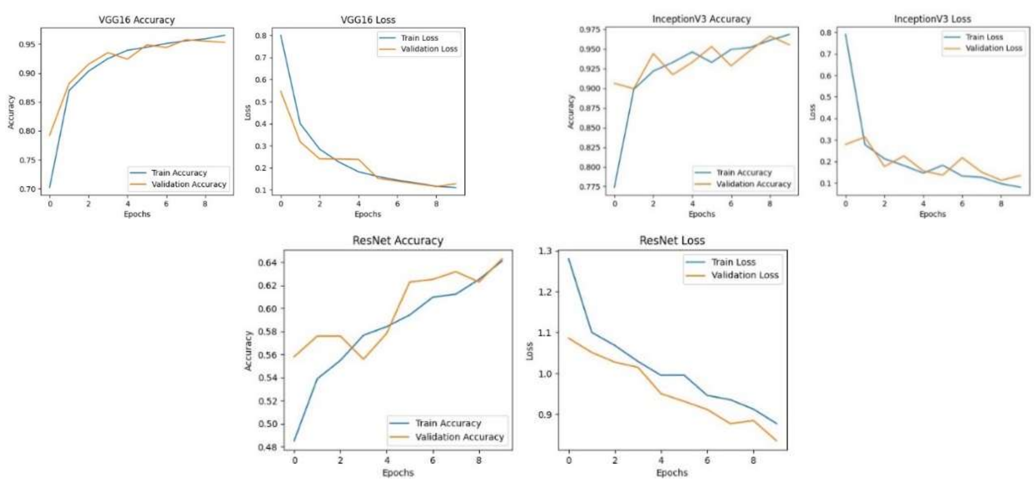

Figure 8: The loss per epoch and accuracy on training and validation datasets for VGG16, Inceptionv3 and ResNet

Fig. 8 provides a comparative analysis of the loss per epoch and accuracy metrics for the three neural network architectures: VGG16, Inceptionv3, and ResNet. This figure offers a side-by-side comparison of their training and validation performance, helping to evaluate the effectiveness of each architecture in the study.
As per the comparison given in Table 2, the InceptionV3 model demonstrated the highest validation accuracy at 96%, outperforming both the VGG16 and ResNet50 models, which achieved accuracies of 94% and 64%*,

respectively. The comparatively lower accuracy of the ResNet50 model, at 64%, could be attributed to several factors, including the training duration of 10 epochs, which might have limited its ability to converge fully. Further investigation and experimentation are needed to pinpoint the exact causes and potential optimizations for improving ResNet50's performance in this specific.

*In the low ResNet50 accuracy results, it is pertinent to note that our study deliberately maintained consistency in the number of training epochs across the different models as part of a comparative study and to adopt a practical approach to disease detection.

TABLE II. COMPARISON FOR VALIDATION ACCURACY FOR ALL THREE MODELS.

Model	**Validation Accuracy**
VGG16	94%
ResNet50	64%
InceptionV3	96%

The results of the study, showcasing validation accuracies of 94%, 64%, and 96% for the VGG16, ResNet50, and InceptionV3 models, respectively, position the approach competitively in comparison to prior published methods. Notably, the accuracies rival or surpass those reported in several cited studies. For instance, Juncheng Ma et al. achieved a robust 93.4% accuracy using deep convolutional neural networks (DCNN) for cucumber disease recognition. The study builds on this benchmark, emphasizing the effectiveness of the YOLO and CNN-based approach for disease detection in apple plant leaves. Similarly, Konstantinos Ferentinos reported an impressive 99.53% success rate in identifying plant diseases using CNNs, aligning with the use of ResNet, VGG16, and InceptionV3 models. The application of deep learning in plant disease detection, as highlighted in the study, aligns with the broader trend emphasized in various literature reviews. Specifically, Andreas Kamilaris and Francesc X. Prenafeta-Boldú's survey and Jun Liu and Xuewei Wang's review underscore the superiority of deep learning over traditional methods, offering high accuracy in diverse agricultural contexts. The study further contributes by focusing on the specific context of apple plant leaf disease detection, building on the collective insights from these comprehensive reviews and specific studies. Additionally, this work is aligned with the exploration of computer vision applications, as demonstrated by Chai Ali, Li Baoju, et al.'s study on tomato foliage disease recognition. This collective comparison positions the study within the evolving landscape of deep learning applications in plant disease detection, highlighting promising outcomes and the ongoing quest for enhanced accuracy and efficiency in this field. The table 3 compares different methodologies used and results obtained by other authors.

TABLE III. A COMPARISON BETWEEN RESULTS AND METHODOLOGIES FROM DIFFERENT AUTHORS

Author	Dataset Used	Problem Addressed	Technique Used	Performance (Accuracy)
Juncheng Ma et al.	Cucumber Disease Images	Cucumber Disease Recognition	Deep Convolutional Neural Networks (DCNN)	93.4%
Our Study	PlantVillage	Apple Plant Leaf Disease Detection	InceptionV3	96%
Konstantinos Ferentinos	Open Database with 87,848 Images	Plant Disease Detection and Diagnosis	Convolutional Neural Networks (CNNs)	99.53%

V. CONCLUSION

The study successfully introduced an image processing-based approach for precise detection of deformities in plant leaves, focusing on applications in precision agriculture. Leveraging Digital Image Processing (DIP) techniques, we pre-processed plant leaf images sourced from the Plant Village dataset and trained three deep learning models—VGG16, ResNet50, and InceptionV3—to identify diseases such as scab, rot, and rust in apples, alongside healthy leaves. The evaluation demonstrated high accuracy across the trained models, each exhibiting varying degrees of effectiveness. Additionally, we developed a user-friendly graphical user interface (GUI) to facilitate easy and convenient disease detection using the trained models.

This study holds significant real-life applications, particularly in the realm of precision agriculture. The ability to accurately and efficiently detect plant diseases through image processing and deep learning models contributes to early disease identification and targeted intervention. Precision agriculture benefits from such technologies by enabling farmers to optimize resource utilization, enhance crop management strategies, and minimize the use of pesticides through targeted treatment. The user-friendly GUI further extends the practicality of the system, making it accessible for individuals without extensive technical expertise. This system aligns with the growing demand for technology-driven solutions in agriculture, offering a valuable tool for farmers to improve crop yield and reduce environmental impact.

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