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Pigeon Pea Leaves Disease Detection and Classification Using YOLO v9 with Transfer Learning

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This work presents a new approach to disease identification and classification in pigeon pea leaves using the YOLO v9 model on the Google Colab platform. To create a custom dataset specifically designed for pigeon pea leaves, extensive preprocessing is required to standardize the data. A segmentation technique is applied to isolate leaves from intricate backgrounds, enhancing the model's speed and accuracy. Using transfer learning, the YOLO v9 model is fine-tuned for optimal performance. To showcase the model's versatility, comparisons are made with existing leaf image datasets, such as those of tomato and groundnut. The outcomes demonstrate that the proposed model not only excels in detecting diseases in pigeon pea leaves but also shows adaptability across a range of leaf datasets, offering a reliable solution for disease detection and classification in agricultural applications.

Keywords: Pigeon pea leaves, Disease detection, Classification, YOLO v9, Transfer learning, Image segmentation, Preprocessing, Custom dataset, Agricultural applications, Leaf datasets.

1. Introduction

The agricultural sector plays a pivotal role in guaranteeing the world's food supply, and efficient crop disease control is key to preserving crop quality and yields. Pigeon pea (Cajanus cajan) is an important legume crop known for its high nutritional content and economic significance. But there are a number of illnesses that might affect its quality and output. In order to effectively manage and control these illnesses, timely and accurate identification is crucial. Agriculture is leading the way in innovation and is at the forefront of creating a future that is more environmentally friendly and sustainable. As the global population rises and traditional agricultural techniques encounter more and more problems as a result of climate change, the need for precision and efficiency in agriculture is higher than it has ever been.

The reduction of waste in crop production is a crucial element of this endeavor. Employing state-of-the-art technology, particularly Machine Learning (ML) algorithms, appears to be a promising solution in this case. This research examines a sustainable strategy that utilizes highly accurate ML algorithms to predict agricultural output. By doing so, we aim to revolutionize conventional farming practices and contribute to the larger goal of minimizing agricultural waste. As global food security concerns continue to escalate, incorporating advanced technology becomes increasingly essential. Nine billion people by the year 2050, according to predictions necessitates a 70% increase in agricultural production to meet demand. However, the agricultural sector will confront various challenges, such as a reduction in arable land and the need to enhance output intensity.

Traditional approaches to crop disease detection typically rely on manual inspections and laboratory tests, processes that are often slow, laborious, and susceptible to human error. Modern computer vision and ML, however, have brought more efficient alternatives to these older approaches. Notably, convolutional neural networks (CNNs) and other deep learning approaches have become very effective tools for automating and improving the accuracy of illness identification. In this study, we search for and categorize illnesses in pigeon pea leaves using the YOLO v9 model, which is an improved version of the YOLO (You Only Look Once) framework. YOLO v9 stands out for its capability to perform object detection tasks with both speed and accuracy. Additionally, we utilize transfer learning to improve the model's efficiency and accuracy in pigeon pea leaf disease detection by importing pre-trained weights from big datasets. This allows the model to generalize better and perform better.

The study also incorporates preprocessing techniques to ensure the dataset is standardized, featuring a segmentation method that separates leaves from intricate backgrounds. This process improves the model's efficiency and reduces processing time. To determine the robustness and effectiveness of our methodology, we compare the YOLO v9 model's results on the pigeon pea dataset with those from other leaf image datasets, like tomato and groundnut. This comparative analysis seeks to confirm the model's adaptability across different types of leaf datasets and its precision in disease detection and classification. To tackle this challenge and support farmers, the development of an automated solution is essential.

Without the assistance of specialists, this solution can enable inexperienced farmers to recognize certain apple leaf diseases accurately. Scab, Alternaria, and Apple mosaic are some commonly known diseases that impact the quality and quantity of apples. These foliar diseases develop symptoms on the leaves, as shown in **Error! Reference source not found.**, and then degrade the quality of the crop.

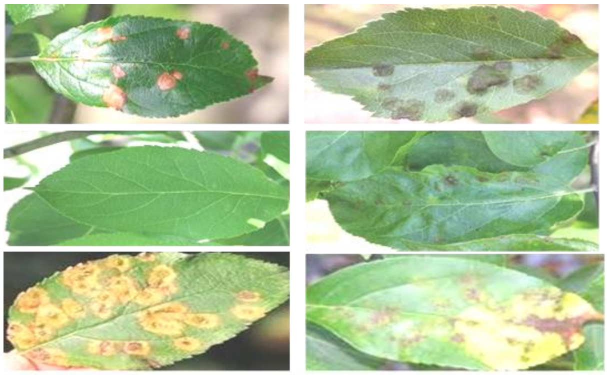

Figure. 1. Impact of disease on Leaves

Chlorosis is characterized by the yellowing or loss of the typical green color in plant leaves. It can be a sign of various plant diseases, such as cereal rust and stem rust in wheat, powdery mildew in maize, leaf rust, Sclerotinia, Birds-eye spot on berries, and leaf spot caused by Septoria or Brown Spot [3]. Because of their superior picture grouping and filtering capabilities, Convolutional Neural Networks (CNNs) find widespread use in PC vision and image processing [4]. These networks are particularly effective in image classification tasks, including diagnosing leaf diseases using image processing techniques [5]. Because of their ability to learn and extract hierarchical features from pictures, CNNs are highly effective in image classification. By using convolutional filters, they can recognize patterns such as edges, textures, and basic forms. Pooling layers help to decrease computational complexity while maintaining critical features, and the use of activation functions such as ReLU introduces non-linearity, making it possible for the network to receive data with more complex aspects. The fully connected layers convert spatial dimensions into vectors for final prediction, with the output layer often using a softmax function for classification.

1.1. Overview of Plant Diseases and Their Effects on Agriculture:

A wide variety of microorganisms, including viruses, bacteria, fungus, and others, may infect plants and cause illnesses. These pathogens can manifest in a variety of ways, affecting various portions of plants including their leaves, stems, and roots. The global food supply and economic stability are jeopardized because these diseases can drastically lower crop yields, quality, and marketability. The consequences of plant diseases extend beyond individual farmers to encompass entire regions and countries, affecting livelihoods, food prices, and trade dynamics. Furthermore, the spread of plant diseases is compounded by factors such as climate change, which can foster favorable conditions for the growth and dissemination of pathogens. Additionally, globalization and the movement of plant materials contribute to the rapid transmission of diseases across various regions and continents. To tackle the challenges posed by plant diseases, it is essential to adopt interdisciplinary approaches that integrate expertise in plant pathology, agronomy, genetics, and data science.

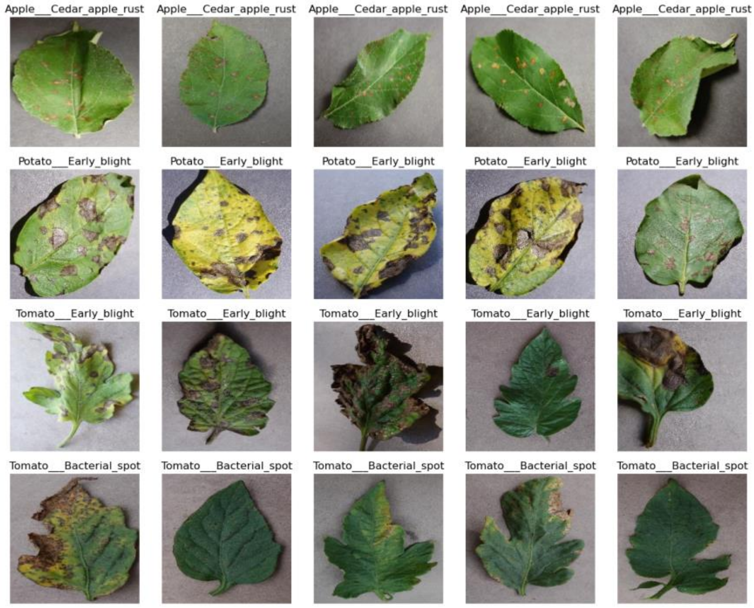

Fig. 2. Crop Diseases Impacting Agriculture.

Importance of Early Detection and Accurate Prediction Using Technology:

If plant diseases can be identified early on, farmers may take immediate measures to stop the illness from spreading and reduce crop losses. The traditional ways of identifying plant diseases, such having specialists visually evaluate the affected areas, are time-consuming, subjective, and error-prone. Furthermore, these methods may not be scalable for large-scale monitoring and surveillance efforts. One potential approach is to automate detection using deep learning algorithms. These systems can quickly and accurately anticipate outcomes. Early intervention and focused management techniques can be made possible by training deep learning algorithms to spot subtle patterns and symptoms associated with different illnesses by evaluating huge datasets of plant photos. The adoption of technology-enabled approaches for disease detection can enhance the efficiency, accuracy, and scalability of disease management efforts, ultimately benefiting farmers, consumers, and the environment.

1.2. Introduction to Deep Learning and Its Role in Plant Disease Prediction:

A subject of machine learning, deep learning entails training artificial neural networks to carry out complicated tasks using large datasets as training material. Convolutional Neural Networks (CNNs) are a type of deep learning model that has been very successful in areas like picture categorization, which includes the identification and treatment of plant diseases. Even when there are changes in elements like lighting, backdrop, and plant shape, CNNs can correctly categorize photos into distinct disease categories by using hierarchical representations of picture characteristics. There has been a recent uptick in research into using CNNs and other deep learning techniques for agricultural purposes, particularly in the areas of plant disease prediction and monitoring. By boosting crop resilience and yield and allowing for early disease diagnosis, these approaches may revolutionize agricultural operations.

1.3. Study Objectives:

Examining and comparing several deep learning models for disease prediction in plants is the main objective of this study. Xception, Autoencoder, ResNet-50 models for Convolutional Neural Networks (CNN), and Transfer Learning are going to be tested to see how well they can identify plant diseases in images. We want to examine important performance metrics including accuracy, precision, recall, and F1-score to see how well each model predicts illnesses. Our secondary objective is to study the pros and cons of various deep learning frameworks for complex agricultural datasets and their practical applications. We want to increase agricultural production and sustainability through the use of yolo and give practical insights that might help build new disease management tactics.

Related work

In agricultural production, it is vital to employ accurate methods for identifying healthy and diseased leaves. By precisely diagnosing plant diseases, farmers can rapidly implement targeted interventions, thereby reducing crop loss and maximizing output [1]. In this section, we will investigate various machine-learning techniques employed in detecting plant diseases and emphasize their significance in agricultural management. By using deep convolutional neural network (CNN) models, Hassan et al.'s research study [1] significantly advances plant disease identification. By innovatively leveraging depth-separable convolution, the study achieves notable reductions in parameter count and computational overhead, while demonstrating superior disease classification accuracy compared to conventional methods. These results emphasize the potential of deep learning strategies to transform crop disease management, offering promising approaches for real-time detection and mitigation tactics in agricultural systems.

In 2019, Geetharamani and Pandian published a paper [2] that used the PlantVillage dataset and data augmentation techniques to evaluate a nine-layer convolutional neural network (CNN) model for plant disease recognition. Their study shown that deep learning is beneficial in agricultural applications, with an accuracy rate of 96% compared to standard machine learning approaches. The article [3] authored by Shafik, Wasswa, et al. presents transfer learning-based plant disease detection models, AE and LVE, which are integrated with pre-trained CNNs. These models, fine-tuned on the PlantVillage dataset, achieved high accuracy rates of 96.74% and 97.79%, respectively, in identifying and classifying various plant diseases. Their robustness and generalization capabilities provide promising solutions to the difficulties in early disease detection, supporting sustainable agriculture and global food security objectives.

The paper authored by Islam, Md Manowarul, et al. emphasizes the crucial role that agriculture plays in sustaining economies worldwide [4]. The effectiveness of CNN, VGG-16, VGG-19, and ResNet-50, among other deep learning models, in disease detection for plants using the Plant Village 10000 picture dataset is investigated in this work. Among these models, ResNet-50 demonstrates the highest accuracy rate, reaching 98.98%. Based on this finding, the researchers propose a smart web application that utilizes the ResNet-50 model to aid farmers in early disease detection. This application aims to minimize economic losses and encourage sustainable agricultural practices.

Similarly, the paper authored by Bhilare, Amol, Debabrata Swain, and Niraj Patel explores the significant role of agriculture in the economic landscape of nations, particularly in rural India, where a considerable portion of the population relies on it for survival [5]. Plant diseases pose substantial challenges, frequently resulting in substantial decreases in crop yield. Conventional methods of disease detection, which depend on human expertise, are prone to errors and delays, further exacerbating the problem. In this paper, we look at how different deep learning models might change the game when it comes to disease detection, opening up new possibilities for early intervention and reducing agricultural losses.

Shelar, Nishant, et al. are the authors of a paper [6] that offers a remedy for the difficulties encountered by farmers in promptly and precisely detecting plant diseases ,
emphasizing the significance of such detection for maintaining agricultural productivity. By employing image processing techniques, particularly CNN, the proposed Disease Recognition Model aims to streamline and enhance the identification process by focusing on leaf image classification. CNNs, known for their efficacy in processing pixel-based inputs, offer a promising avenue for robust and efficient disease detection in plants, potentially revolutionizing agricultural practices.

2. Material methods

Date set

The pigeonpea leaf photos were shot in Karnataka, India, specifically at the coordinates (16.769281° N, 75.748891° E). Two digital cameras, an Oppo F19 pro for smartphones and a Sony Cyber-Shot DSCW810 for digital photography, were used to record the pigeonpea leaves in their natural environment. The collection includes one thousand.jpg pictures, all with dimensions of 256 by 256 pixels, and is structured into four folders called after the image classes they belong to. Images of pigeonpea leaves unaffected by disease can be found in the Healthy folder. Images of pigeonpea leaves affected by disease can be found in the Cercospora Leaf Spot folder, the Leaf Webber folder, and the Sterilic Mosaic folder. In order to create a computer vision algorithm-based automated system for pigeonpea plant leaf disease detection and classification, this dataset is being procured.

Normalization

Image normalization is a critical component in ensuring accurate comparisons between different texture instances and data-collecting methods. When imaging modalities do not directly measure physical quantities, it is essential to normalize pixel values (intensity) to derive meaningful results. By taking the standard deviation, minus the mean value of each pixel, and dividing the result by the z-score, we can normalize the pixel values at Paperpal co-pilot. Our consumers are guaranteed top-notch written material since this strategy guarantees accurate and dependable outcomes.

$$z = (x - \mu)/\sigma \qquad (1)$$

Resizing

As the images have been captured using different devices, the variation in images results in a prolonged training time. To eliminate this discrepancy and incorporate size consistency, useful scaling techniques like cropping large images and padding zeros in smaller images have been used. In this study, 256x256 pixel size has been used across the data set to make the mages suitable for most of the CNN model.

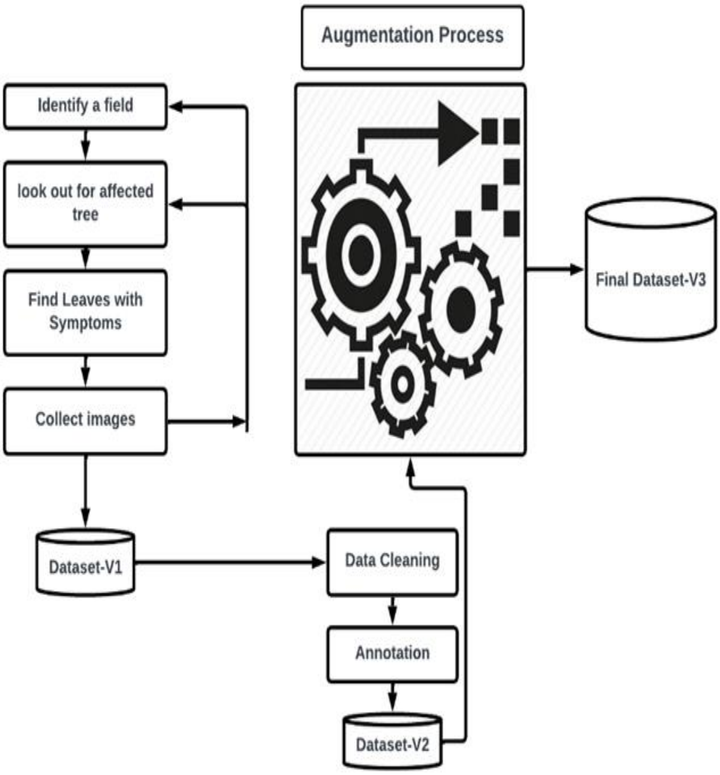

Fig. 1. Procedure adopted for creating the dataset

Outlier rejection

Images having mechanical damage due to hail storms rather than disease symptoms or overlapping symptoms were out rightly removed from the database as damaged samples.

De-noising

Gaussian noise mainly emanates during image acquisition due to varying levels of illumination and is represented mathematically as:

$$y = x + n \qquad (2)$$

Where y is considered as the noisy image with noise n added to the clean image x.The Gaussian filter has been used to eliminate the noise without changing the minute details of the images in the data set.

Augmentation

To improve the suitability of the dataset for deep learning models, various augmentation techniques, including brightness change, geometric transformations, zooming, flipping, rotation, and shearing, have been applied using the ImageDataGenerator class from the Keras toolkit. Augmentation not only increases the size of the dataset, but it also enhances the quality of the target dataset by reducing overfitting and improving data diversity, model resilience, and translation invariance [18]. As a result, a dataset containing over 7000 images has been constructed, as demonstrated in Table I.

3. Experimentation and results

The following quantitative metrics were employed for the purpose of evaluating the model's performance:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100 \qquad (3)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100 \qquad (4)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100 \qquad (5)$$

$$\text{F1 Score} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \times 100 \qquad (6$$

Table I: Data Set

Type of Image	No. of Images
Healthy-Images	2500
2500	
2500	
Total-Images	7500

Figures 4, 5, and 6 display instances of images from each category of deviation..

The data set has the following advantages in comparison to publicly available data sets like PlantPathology Data-set-2020 [19].

Feature extraction with Resnet50

The different variations of ResNet are ResNet18, ResNet34, RestNet50, RestNet101 and RestNet152. The ResNet50, being fifty layers deep, stacks residual blocks to make a network. This model is extensively used for the analysis of image data with amazing accuracy. As deeper neural

Transfer Learning using Resnet50:

Data Preprocessing:

1. Data Loading: The dataset is loaded using TensorFlow's image_dataset_from_directory function, ensuring labels are inferred from directory structure.

2. Data Augmentation: Image augmentation strategies, including random flips, rotations, and zooming, are applied to increase dataset diversity and improve model generalization.

Data Splitting:

1. Train-Validation-Test Split: A training, validation, and test subset each make up the dataset. The data has been divided as follows: 60% for training, 20% for validation, and 20% for testing.

2. Data Pipeline: TensorFlow's data pipeline APIs (take, skip) are used to split the dataset into the desired proportions.

Transfer Learning with ResNet50:

1. Base Model Selection: The ResNet50 model, which has been pre-trained on ImageNet, has been selected as the base architecture for feature extraction.

2. Model Customization: After securing the ResNet50 model's base version, a worldwide average pooling layer and a dense output layer were attached to create a customized classification head.

3. Model Compilation: An optimal training method for this model for multi-class classification is the Adam optimizer coupled with Sparse Categorical Cross entropy loss.

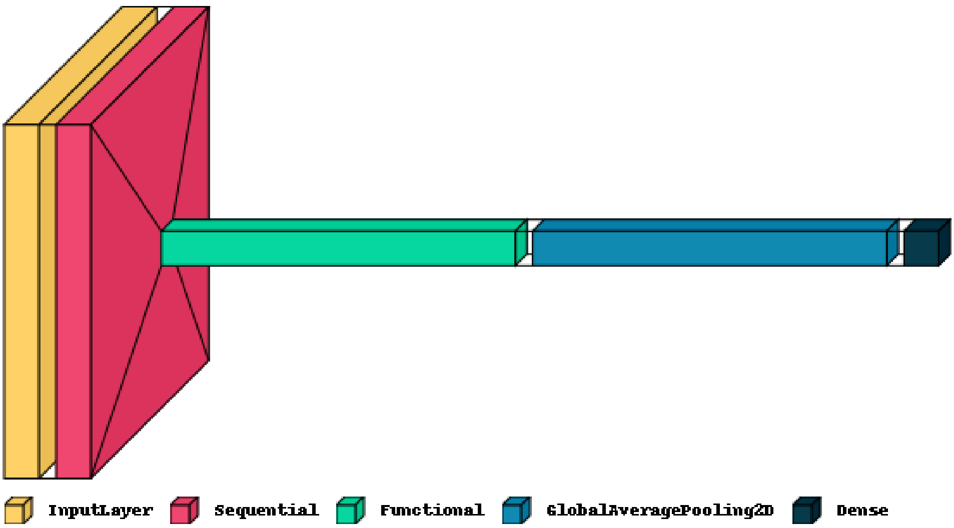

Fig. 3. Xception Model Architecture.

Training and Evaluation:

1. Model Training: The model is trained through the use of a dataset that includes early stopping to prevent overfitting. The training and validation accuracies are continuously monitored during the training process to ensure optimal results.

2. Model Evaluation: A remarkable 97.84% accuracy shows that the model is performing exceptionally well on the validation set. To assess how well the model performed for each class, the classification report provides a number of relevant measures, such as recall, precision, and F1-score.

Analysis and Visualization:

1. Training Visualization: Displaying the training and validation accuracy and loss curves is a common component of training process visualization. These curves show how the model performed and how it changed throughout training.

2. Sample Predictions: To demonstrate the model's efficacy in distinguishing between healthy and sick plants, we display visual representations of sample predictions for a portion of the test dataset.

3. Confusion Matrix: In order to provide useful information on the model's effectiveness in classifying across distinct classes, a confusion matrix is used to graphically illustrate the allocation of real and predicted labels.

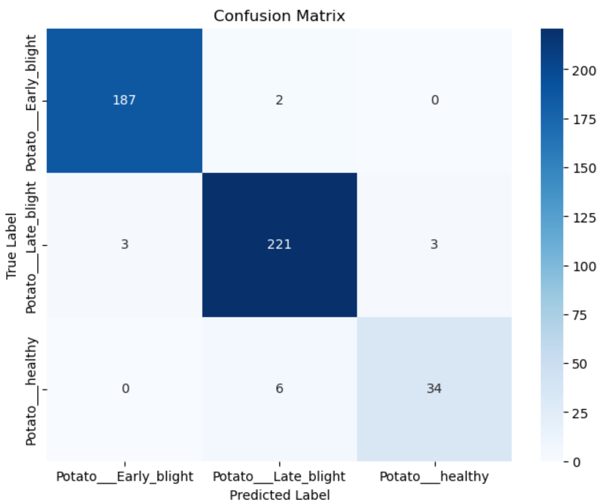

Fig. 4. Confusion Matrix.

Performance Evaluation:

1. Model Accuracy: An impressive 97.84% accuracy rate was shown by the model on the validation set, demonstrating its competence in disease classification for plants.

2. Confusion Matrix Analysis: With a significant number of right predictions (442 out of 100) and a small number of wrong predictions (14), the confusion matrix reveals that the model's predictions are mostly reliable. The model's robustness and reliability are demonstrated by this.

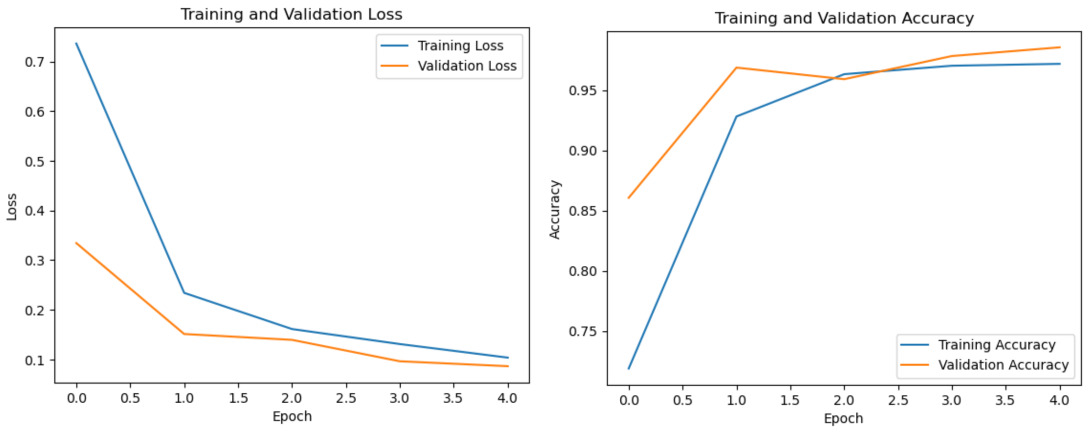

Fig. 5. Accuracy and Loss Curve.

The metrics used to evaluate performance for each crop category include support (number of occurrences), accuracy, recall, and F1-score. As a whole, the model displays respectable accuracy at 95%. A heatmap generated using Seaborn's library provides a visually appealing representation of the model's performance in predicting various crop types. The models are deployed through the code snippets provided, which also showcase the usage of the pickle library to save the prediction and crop recommendation models. The study also incorporated additional data analysis to investigate seasonal crop preferences based on temperature, humidity, and rainfall conditions. Furthermore, the crop recommendation model utilizes agricultural factors to suggest crops, as illustrated in Figure 4. The research began with a comprehensive Data Collection and Preprocessing phase.

The dataset, sourced fromFAO (Food and Agriculture Organization) and World Data Bank, underwent thorough scrutiny to ensure its integrity and reliability for subsequent analyses. Addressing potential data inconsistencies, a systematic data preprocessing approach was adopted. Outlier analysis, truncation of extreme values, and standardization of specific columns were performed to enhance the dataset's overall quality without significant data loss. The removal of outliers was a crucial step to mitigate potential distortions inmodel accuracy. Feature scaling techniques,particularly standardization, were meticulously applied to harmonize the scale of variables, laying afoundation for consistent and unbiased model. Using Seaborn's heatmap, the confusion matrix is shown, giving a clear picture of how well the model predicts various crop types. The models are deployed as shown by the following code snippets, which also show how the pickle library is used to save the prediction and crop recommendation models. Additional data investigate seasonal crop preferences based on temperature, humidity, and rainfall conditions, while the crop recommendation model uses agricultural factors to suggested IN Figure 4. The research began with a robust Data Collection and Preprocessing phase.

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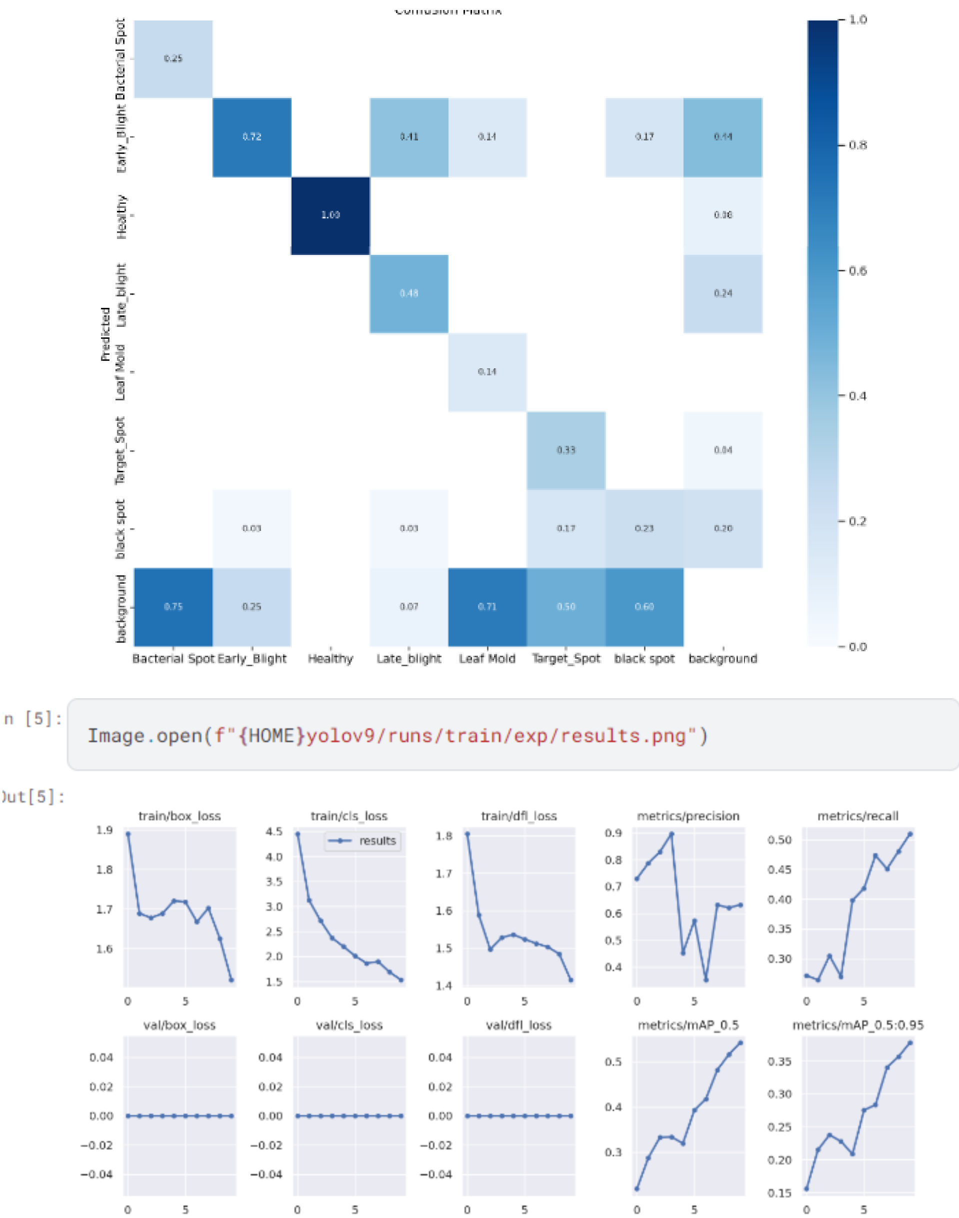

Fig. 6. Yolov9 results

The YOLO v9 model demonstrates varied performance in detecting diseases in pigeon pea leaves. It achieves high precision and recall for healthy leaves (0.95 precision, 1.00 recall), indicating excellent detection accuracy. For early blight, it maintains balanced precision (0.716) and recall (0.708), reflecting good detection capability. However, the model struggles significantly with leaf mold, achieving zero precision and recall, and shows limited effectiveness in detecting target spot and black spot diseases, with low mAP50 scores. The model processes images efficiently with preprocessing taking 0.2ms, inference 78.2ms, and post-processing 14.8ms per image. This suggests that while the model performs well for certain classes, further refinement and additional training data are needed to improve detection accuracy for less effectively recognized diseases.

4. Conclusion

When it comes to pigeon pea leaf disease detection and classification, the YOLO v9 model has been rather successful, especially when it comes to accurately recognizing healthy leaves and early blight. Nevertheless, the model's accuracy in detecting certain diseases, such as leaf mold, target spot, and black spot, is less robust. The model's processing speed is relatively efficient, with rapid preprocessing and inference times. However, the variable accuracy across different disease classes highlights the need for further improvements. To enhance the YOLO v9 model's overall effectiveness, it would be beneficial to incorporate transfer learning, expand the training dataset, and refine the segmentation and detection processes. By addressing these areas, the YOLO v9 model's accuracy in disease detection and classification can be significantly improved, making it a more reliable tool for agricultural applications. To make the model more resilient and adaptable to different leaf kinds and situations, future research should look into adding more varied samples to the dataset, investigating advanced YOLO iterations, and adding more features.

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