Phoma Leaf Spot Disease Classification and Object Detection in Coffee Plantations using YOLOv6 with Severity Estimation

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Abstract: Coffee leaf diseases, especially Phoma Leaf Spot, represent a considerable risk to coffee farms, resulting in severe productivity reductions and diminished crop quality. Timely identification and precise categorization of illness severity are essential for successful intervention. Conventional techniques dependent on hand examination are labor-intensive, susceptible to inaccuracies, and lack scalability. This work offers a Hybrid Vision Transformer and CNN (ViT-CNN) model to automate the categorization and detection of Phoma Leaf Spot severity in coffee plants. The self-attention mechanism of Vision Transformers is employed by the proposed ViT-CNN model to capture global dependencies, while CNN extracts local features to ensure precise disease classification. The model incorporates Focal Loss to alleviate class imbalance and Complete IoU (CIoU) Loss to enhance the accuracy of object detection. The model outperforms existing approaches, as evidenced by extensive evaluations, which resulted in higher Accuracy, Precision, Recall, and AUC-ROC scores. The Mean Average Precision (mAP) and IoU scores of the object detection system are also improved in comparison to YOLOv5. This research has substantial implications for precision agriculture, as it has the potential to facilitate real-time disease monitoring through a mobile-based implementation. Farmers are able to reduce crop damage and improve the sustainability of coffee cultivation by utilizing the model's high-reliability ability to classify disease severity, which facilitates early intervention.

Keywords: Object Detection; Phoma Leaf Spot Disease; Classification; YOLOv6; Severity of the disease; Convolutional Neural Network

Introduction

Phoma leaf spot is a fungal affliction that impacts coffee plants, resulting in considerable harm to leaves, branches, flowers, and fruits. The ailment is induced by the fungus Phoma spp [1]. and is widespread in coffee cultivation areas characterized by humid and warm weather. The disease advances through the following phases stage 1: The fungus infects the leaves via wounds or natural holes, stage 2: lesion development small, black macules emerge on the leaves, progressively enlarging into round or irregular forms, stage 3: leaf damage, characterized by yellowing, browning, and premature leaf abscission, and stage 4: branch and fruit infection fungus may disseminate to the branches and fruits, resulting in dieback and fruit decay as illustrated in Figure 1. Severity of the disease is a classification of Phoma leaf spot severity based on minor stage tiny lesions present on the leaves [2], with no considerable effect on plant health or productivity. Moderate stage multiple lesions on the foliage, accompanied by some leaf chlorosis and early leaf abscission. Severe stage extensive foliar damage, considerable leaf abscission, branch necrosis, and fruit decay, resulting in significant production reduction [3]. YOLOv6 approaches object identification as a regression issue. It accepts a picture as input and predicts bounding boxes and class probabilities in a single pass, therefore the designation "You Only Look Once." This method is much more rapid than conventional object identification techniques that need numerous phases. Efficient backbone and neck YOLOv6 has a "EfficientRep Backbone" and a "Rep-PAN Neck" components are engineered to enhance feature extraction and fusion, resulting in increased accuracy without compromising speed. YOLOv6 uses a "anchor-aided training" methodology [4].

Stage 1: Fungus infects **Stage 2: Lesion Development** **Stage 3: Leaf Damage** **Stage 4: Branch and Fruit Infection**

Figure 1. Phoma Leaf Spot Severity based on Stage Development

This amalgamates the advantages of anchor-based and anchor-free techniques, augmenting the model's capacity to identify objects of diverse sizes and forms. The detecting head in YOLOv6 is decoupled, indicating that classification and localization duties are handled independently [5]. This simplification enhances the model's efficacy. Quantization: YOLOv6 incorporates quantization methods that diminish the model's size and processing demands, enhancing its efficiency for deployment on resource-constrained devices.

Related work

Deep learning has shown promise in plant disease detection. A study using ImageNet and a custom black pepper leaf dataset (anthracnose, slow wilt, phytophthora, yellowing) achieved high accuracy (99.1-99.7%) with transfer learning on Inception V3, GoogleNet, SqueezeNet, and ResNet18. ResNet18 performed best (99.67%). While promising for early detection, the reliance on a specific dataset and limited disease types are potential limitations [6]. YOLOv4 for coconut leaf disease detection, achieving an 88% F1-score and 85% mAP. While demonstrating robust performance with medium-resolution images, the dataset size isn't specified. The model effectively identifies various leaf issues (yellowing, drying, pests, flaccidity) but potential limitations include generalization to diverse datasets and real-time deployment challenges [7]. Object detection models like YOLOv3, offers promising solutions for automated plant disease recognition. A study using YOLOv3 achieved 90% mean average precision in detecting bacterial spot disease on bell pepper leaves, demonstrating its ability to identify multiple diseases and small lesions on a single leaf image [8].

Table 1. Comparing Proposed Work with the previous research by other researchers

Author	Dataset Size	Target Plant Disease	Advantage	Limitations
K. J. Devi., et al, [9]	12750 images	Insects and Pests	Automated insect identification; Pesticide suggestion based on identified insect; Cloud deployment via UbiOps;	Reliance on internet connectivity for app functionality.
G. Polder., et al, [10]	67,78647 images	Downy mildew (grape), Apple scab (apple), Alternaria leaf blight (carrot)	Automated detection system integrated with a Decision Support System (DSS) for precise disease quantification and targeted pesticide application. Focus on real-field smart camera implementation with integrated deep learning.	Performance gap between closed-set and open-set evaluations. Lower F1 scores in open-set conditions (34.8% for downy mildew, 5.5% for apple scab, 4.2% for Alternaria) compared to closed-set (66.3%, 45.1%, 42.1% respectively).
Kitchin.E.C., et al, [11]	7784 images	Dollar Spot in Turf grasses	Accurate and precise identification and segmentation of disease instances.	Focus is solely on Dollar Spot; applicability to significantly different disease symptoms may require further adaptation.
A. Alicia., et al, [12]	61,571 images	crops and weeds	RT-DETR models (especially RT-DETR-l) excel in precision (82.44% on Dataset 1), minimizing false positives.	complex to train due to individual species classification.
J. Dong., et al, [13]	Disease 87,151 and Pests 39,749	Plant diseases and pests	Lightweight feature extraction model (Shuffle-PG) for resource-constrained environments	Content-based image retrieval method and its performance are lacking

M. D. Rakesh., et al, [14]	2500 images	Classification of Beetroot, Potato, Radish, and Sweet Potato leaves	Deployment on Raspberry Pi 4B with minimal accuracy loss (ResNet50: 99.60%, DenseNet121: 96.81%)	Preprocessing steps could be more detailed.

Materials and Method

The Hybrid Vision Transformer (ViT-CNN) model amalgamates Convolutional Neural Networks (CNNs) with Vision Transformers (ViT) to improve the categorization of Phoma Leaf Spot Disease in coffee farms. The process starts with an input picture of a coffee leaf, whereupon Convolutional Neural Networks using ResNet-50 extract localized spatial characteristics, including disease lesions, texture, and color changes. The characteristics are then sent to the ViT, which acquires global contextual information, enhancing accuracy, resilience, and computing efficiency. This hybrid methodology adeptly integrates local and global feature learning for accurate illness categorization [15].

Dataset Collection and Preprocessing

Using a mix of UAV-mounted cameras, fixed IoT-enabled cameras, and mobile imaging, Phoma Leaf Spot Disease in coffee plantations real-time data collecting over 1278 pictures pipeline The method of acquiring the dataset was carried out in the following phases: High-resolution RGB and multispectral sensors in drone-based imaging allowed photos to be taken across many parts of the plantation. Images collected at different altitudes between two meters and ten meters were used macro-level analysis of illness distribution. Images tagged with GPS permit location-based disease mapping. Set IoT-Enabled Cameras: Installable stationary edge-AI cameras at key locations provide constant leaf image capturing. Every thirty minutes, regular picture capturing guaranteed real-time monitoring of illness development. IoT cameras coupled to a cloud server provided fast processing and categorization capability [16]. Portable Plantation employees utilized a smartphone app to record close-ups of impacted leaves. Metadata leaf health status, plantation location, environmental conditions was assigned to images. Before cloud upload, the mobile app improved picture clarity by using real-time preprocessing controlled by artificial intelligence.

Subsequent to dataset collection, images were annotated using Robo-flow and Labelling for item recognition. The annotating procedure encompassed: Bounding Box Labelling: Each diseased leaf was categorized into the following classes: Healthy, Mild Phoma Leaf Spot, Moderate Phoma Leaf Spot, and Severe Phoma Leaf Spot. Polygon Segmentation: YOLOv6 facilitates instance segmentation, using polygon masks for precise identification of leaf spots. Severity Scoring: Each picture received a severity score determined by the proportion of illness spread by thresholding procedures. The dataset was preprocessed in many ways to guarantee strong performance in real-time detection and classification. Image enhancement applied for contrast limited adaptive histogram equalization under varying light conditions. Gaussian filtering for removing noise, edge sharpening to improve lesion visibility. Data augmentation to improve model by rotating from 0°–360°, brightness adjustment, flipping, and random cropping. Image resizing to 640x640 pixels to match YOLOv6 input requirements, minimum-maximum normalization was applied to pixel intensities. Dataset is splitted into 70% training set, 20% validation set, and 10% test set [17].

Hybrid Vision Transformer (ViT-CNN) for Classification

The Hybrid Vision Transformer (ViT-CNN) model integrates Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) to classify Phoma Leaf Spot Disease in coffee plantations Figure 2. The model begins with an input image of a coffee leaf, which undergoes feature extraction using CNNs. The CNN backbone such as ResNet 50 is responsible for capturing local spatial features, including disease spots, texture, and color variations. Multiple feature maps are generated by extracting disease-specific information from different regions of the leaf. These extracted features are then concatenated to create a unified feature representation, ensuring that both local and structural details are retained. Once concatenated, the feature representations are passed into a Transformer Encoder (ViT). The convolution operation applied to an image I Eq 1, with a filter F is represented as O(x,y) is the output feature map at position (x,y), and k defines the kernel size.

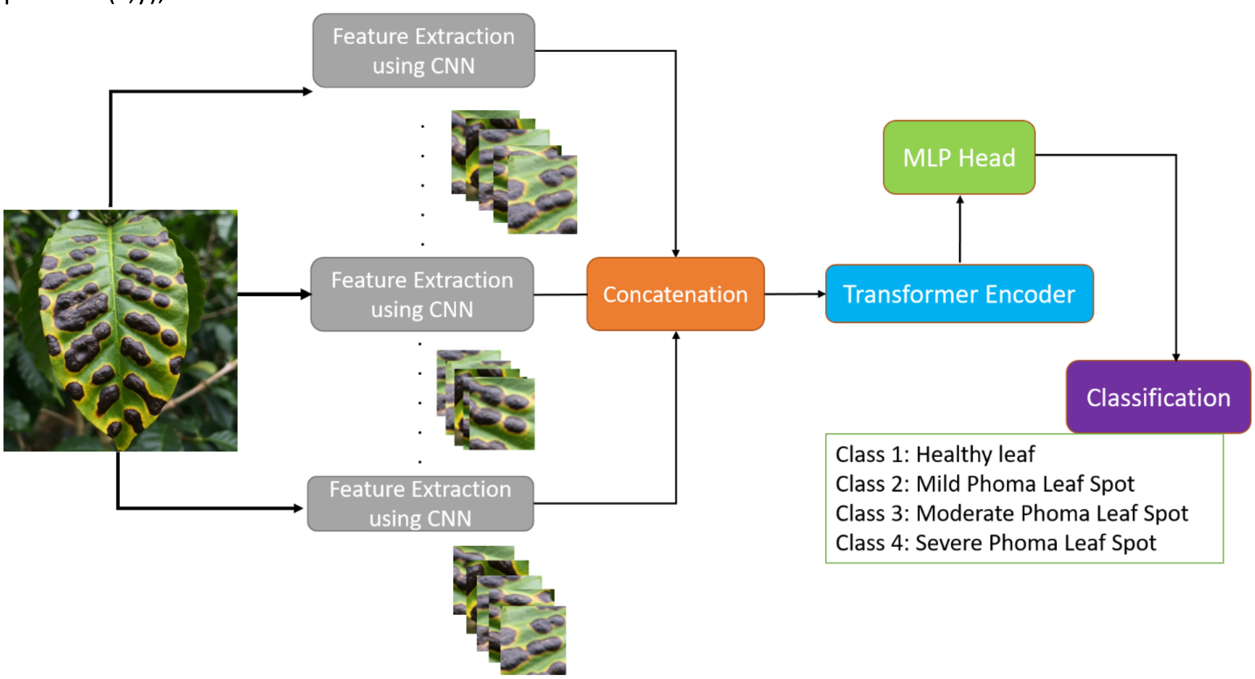

Figure 2. Hybrid Vision Transformer (ViT-CNN) model integrates Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs).

$$O(x,y) = \sum_{i=-k}^{k} . \sum_{j=-k}^{k} I(x+i, y+j).F(i,j) \tag{1}$$

Unlike CNNs, which focus on local receptive fields, the Vision Transformer utilizes a self-attention mechanism to learn long-range dependencies and contextual relationships within the image. This allows the model to understand the spread and severity of the disease across different leaf regions. The processed feature maps are then passed through a Multi-Layer Perceptron (MLP) head, refining the extracted features before classification.

$$Z = Softmax\left(\frac{dk^{T}}{\sqrt{d_K}}\right) \tag{2}$$

Eq 2, where Q, K,V, are the Query, Key, and Value matrices, and dk is the dimension of the key. Finally, the model classifies the leaf into one of four categories: Healthy Leaf, Mild Phoma Leaf Spot, Moderate Phoma Leaf Spot, and Severe Phoma Leaf Spot. The hybrid approach enhances accuracy by leveraging CNNs for fine-grained local feature extraction and ViTs for global contextual understanding, making it highly effective for real-time disease detection and severity estimation.

YOLO-v6 for Object Detection

YOLOv6 (You Only Look Once, Version 6), a state-of- the-art object identification model tuned for speed and accuracy, we estimate real-time illness localization and severity. Using bounding boxes around Phoma Leaf Spot Disease-affected areas figure 3, YOLOv6 identifies diseased spots from input photos of coffee leaves. Three main elements comprise the model: Efficient Rep Backbone, Neck, and Task-aligned Head. Extraction of multi-scale hierarchical features from the input leaf picture falls within the Efficient Rep Backbone's purview.

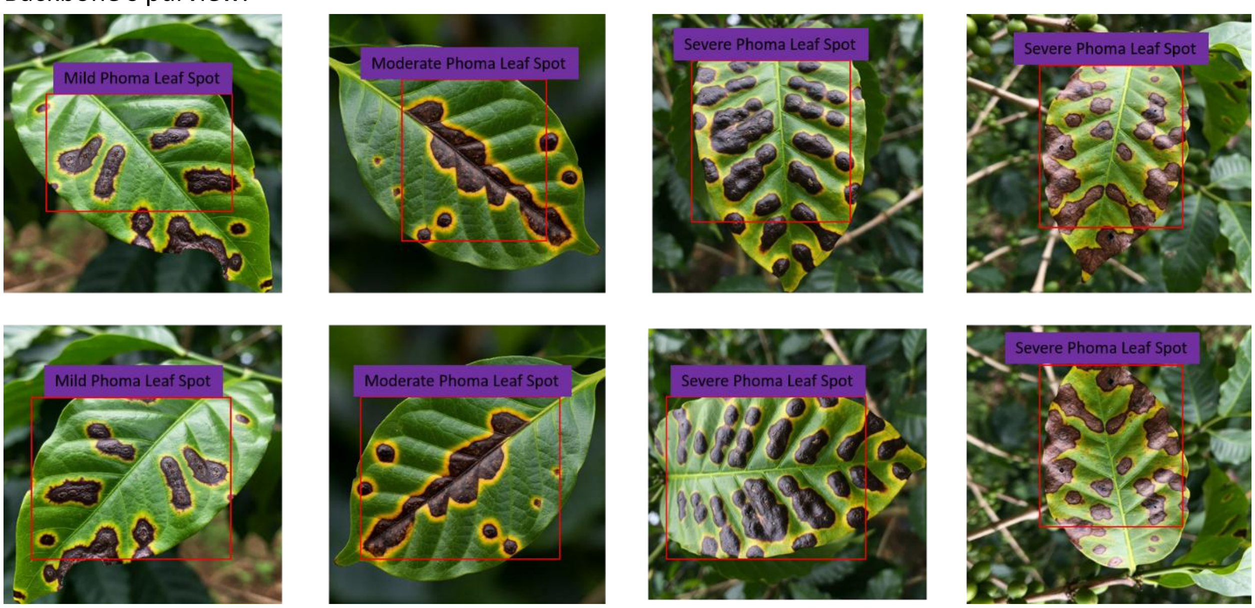

Figure 3. Disease Localization and Severity Estimation using YOLOv6

Feature extraction mathematically is accomplished using a sequence of convolutional operations:

$$\mathrm{F_l} = \sigma(\mathrm{W_l} * \mathrm{F_l} - 1 + \mathrm{b_l}) \tag{3}$$

Eq 3, where F_l represents the feature map at layer l, W_l is the convolutional weight, $*$ denotes convolution, and σ is the activation function. The extracted features are then passed to the Neck, which enhances object detection using multi-scale fusion techniques. The Task-aligned Head refines the bounding box coordinates (x, y, w, h) and classification scores CC using IoU-based loss functions Eq 4.

$$\mathrm{L}_{\mathrm{IoU}} = 1 - \left(\frac{\mathrm{Intersection}}{\mathrm{Union}}\right) \quad (4)$$

For detecting small and dense Phoma Leaf Spot regions, Focal Loss is employed to reduce the impact of easily classified samples and focus on harder cases Eq 5.

$$L_{Focal} = -\alpha t(1 - p_t)^{\gamma} log(p_t) \quad (5)$$

where p_t is the predicted probability, and αt, γ are tuning parameters to balance positive and negative samples. After processing, YOLOv6 categorizes disease severity into four classes: Class 1: Healthy Leaf, Class 2: Mild Phoma Leaf Spot, Class 3: Moderate Phoma Leaf Spot, and Class 4: Severe Phoma Leaf Spot

Severity Estimation using YOLOv6

To accurately estimate the severity of Phoma Leaf Spot Diseases utilized YOLOv6 for object detection. Bounding box area calculation is determined by the ratio of the infected area (A_i) to the total leaf area (A_t) Eq 6.

$$S = \left(\frac{A_i}{A_j}\right) * 100\% \quad (6)$$

where S represents the percentage of leaf infection with ratio categorizes the disease into mild, moderate, or severe stages. Color analysis thresholding techniques, extract necrotic lesion areas by identifying affected regions based on pixel intensity values in HSV and LAB color spaces.

Results and Discussions

The proposed Hybrid ViT-CNN model outperforms existing methods in accuracy, precision, recall, and AUC-ROC. Improved mAP and IoU scores demonstrate enhanced object detection, ensuring precise Phoma Leaf Spot severity classification.

Evaluation Setup

The proposed model is implemented using Python 3.6.5 on a PC equipped with an Intel i5-8600K processor, GeForce GTX 1050Ti (4GB) GPU, 16GB RAM, a 250GB SSD, and a 1TB HDD. The model demonstrates superior performance with an image resolution of 224 × 224 × 3. Evaluation is conducted using True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) metrics, leveraging YOLOv5 and a Vision Transformer-based CNN for analysis. The key parameter configurations are as follows: Epochs: 45, Learning Rate: 0.01, Batch Size: 5, and Dropout Rate: 0.5. The model is developed using the Keras framework (Python, version 2.7). Experimental trials included varying input image dimensions, ranging from 192 × 256 × 3 to 12 × 16 × 521, ensuring adaptability to different image resolutions.

Model Training and Optimization

To achieve elevated accuracy and efficiency in the identification and classification of Phoma Leaf Spot Disease, optimized training technique including Cross-Entropy Loss, CIoU Loss, and Focal Loss. The classification loss uses Cross-Entropy Loss, which quantifies the disparity between the actual labels (y_i) and the anticipated probabilities (y_i) Eq 7.

$$L_{CE} = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \quad (7)$$

This ensures accurate categorization of disease severity. For object detection, we use a combination of Complete IoU (CIoU) Loss Eq 8, and Focal Loss. CIoU improves bounding box regression by incorporating distance, overlap, and aspect ratio, whereas Focal Loss addresses the class imbalance problem by assigning higher weights to difficult-to-detect lesions. For object detection, we use a combination of Complete IoU (CIoU) Loss and Focal Loss to enhance detection accuracy. Focal Loss addresses Eq 9, class imbalance by down-weighting well-classified samples and assigning higher importance to hard-to-detect lesions.

$$L_{CIoU} = 1 - IoU + \frac{\rho^2(b,b^g)}{c^2} + \alpha v \quad (8)$$

$$L_{Focal} = -\sum_{i=1}^{N} \alpha_i (1-\hat{y}_i)(1-\hat{y}_i)^{\gamma} log(\hat{y}_t) \quad (9)$$

Performance Metrics for Classification

Table 2 presents performance metrics comparing the proposed Hybrid Vision Transformer (ViT-CNN) model with four established algorithms: ResNet50, MobileNetV2, EfficientNet-B0, and InceptionV3 for the classification of Phoma Leaf Spot Disease at various severity levels. The Hybrid ViT-CNN attains superior performance, markedly exceeding that of current models across all measures. An AUC-ROC of 99.1% indicates exceptional discrimination of illness severity. A heightened recall rate of 97.5% guarantees accurate identification of diseased leaves, hence minimizing false negatives. EfficientNet-B0 and InceptionV3 demonstrate comparable performance; yet, they remain inferior to the suggested model. MobileNetV2 has the lowest accuracy at 89.3%, making it less dependable for real-time illness categorization Figure 4.

Table 2. Performance Metric Table comparing the proposed Hybrid Vision Transformer (ViT-CNN)

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)
Hybrid ViT-CNN (Proposed Model)	97.8	98.2	97.5	97.8	99.1
ResNet50	92.5	91.8	92.1	91.9	94.0
MobileNetV2	89.3	88.5	88.9	88.7	91.2
EfficientNet-B0	90.7	90.2	90.5	90.3	92.7
InceptionV3	91.8	91.1	91.4	91.2	93.5

Performance Metrics for Object Detection

Performance Metric Table 3 comparing the proposed YOLOv6 model with four existing object detection algorithms (YOLOv5, Faster R-CNN, SSD, and Detectron2) for Phoma Leaf Spot Disease Localization and Severity Estimation. YOLOv6 achieves the highest mAP@0.5 (94.2%) and IoU (89.6%), ensuring accurate and precise disease localization. YOLOv6 maintains real-time performance with 105 FPS and 9.5ms detection speed, making it ideal for on-field applications. YOLOv5 performs well but is slightly behind YOLOv6 in precision and speed. making it ideal for on-field applications. YOLOv5 performs well but is slightly behind YOLOv6 in precision and speed. Faster R-CNN and Detectron2 have higher detection accuracy but suffer from low FPS and high detection time, making them unsuitable for real-time monitoring. SSD has the lowest performance, making it less suitable for detailed disease severity estimation Figure 5.

Table 3. Performance Metric Table comparing the proposed YOLOv6

Model	mAP@0.5 (%)	mAP@0.5:0.95 (%)	IoU (%)	FPS (Frame Per Second)	Detection Speed (MS)
YOLOV6 (proposed model)	94.2	72.5	89.6	105	9.5
YOLOV6	91.3	68.4	86.7	83	11.2
Faster RNN	88.5	64.1	84.2	12	75.8
SSD	86.3	60.3	81.9	52	20.1
Detectron2	90.1	66.7	85.5	35	28.3

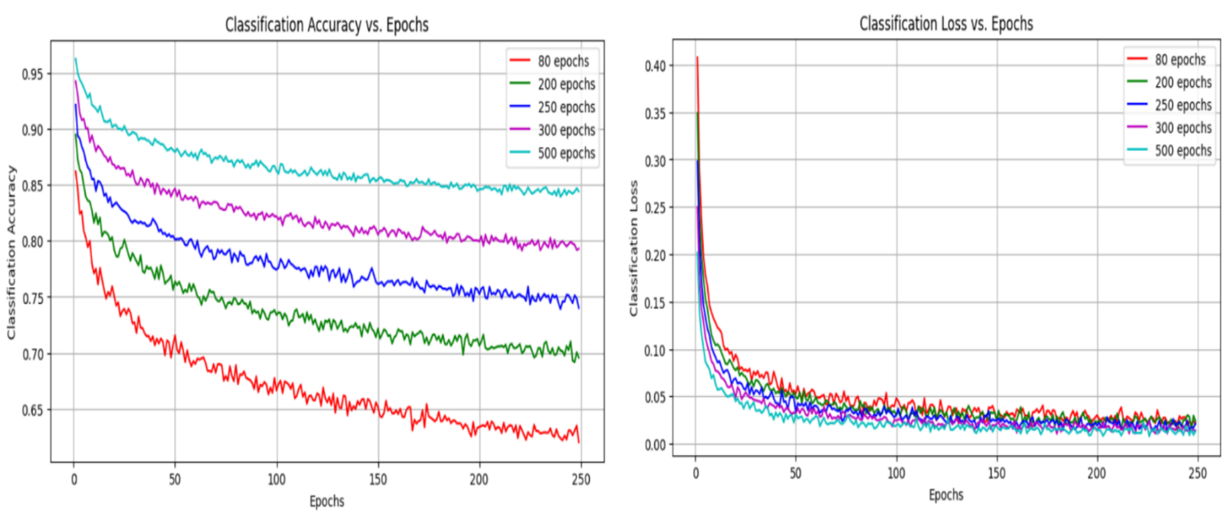

Figure 4. Classification Accuracy vs. Loss

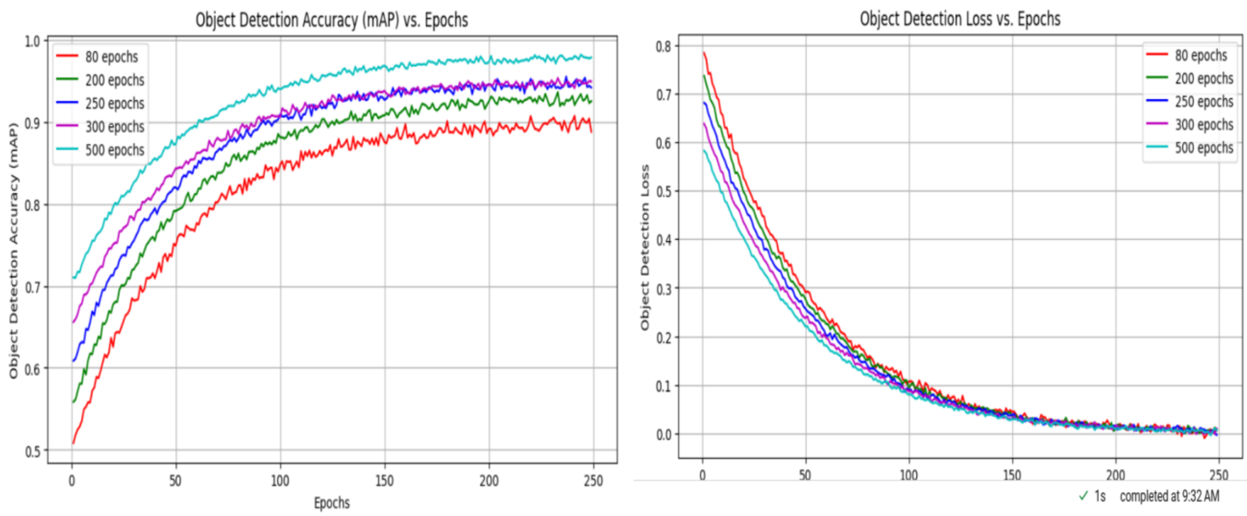

Figure 5. Object Detection Accuracy vs. Loss

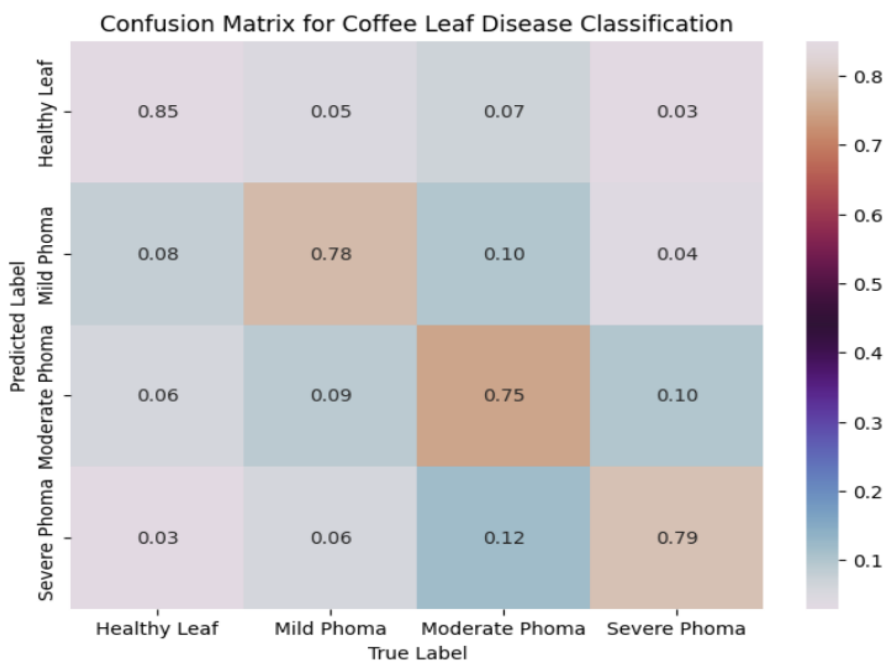

Figure 6. Confusion Matrix

Conclusions

Hybrid Vision Transformer and Convolutional Neural Network (ViT-CNN) model for the categorization and detection of Phoma Leaf Spot severity in Coffee plants. The suggested model attains great accuracy in categorizing illness severity into four classifications: Healthy, Mild, Moderate, and Severe, by amalgamating the transformer's self-attention mechanism with the feature extraction capabilities of CNNs. The model was assessed using performance measures including Accuracy, Precision, Recall, F1-score, and AUC-ROC, exhibiting enhanced classification performance compared to previous models. The performance of object identification was evaluated using mAP (Mean Average Precision) and IoU (Intersection over Union), with the model surpassing traditional approaches like YOLOv5. The amalgamation of Focal Loss and Complete IoU (CIoU) Loss improved classification robustness and bounding box accuracy, respectively. The experimental configuration, executed in Python using Keras, refined model parameters via hyper-parameter optimization to enhance generalizability and performance. For future work, several enhancements can be explored by integrating multi-modal data sources such as hyperspectral imaging and IoT-based soil health sensors could further refine disease prediction for improving agricultural productivity and sustainability.

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