Intl. J. Engg. Sci. Adv. Research 2025 March; 11(1): 1- 4 ISSN NO: 2395-0730

Coffee Leaf Disease Detection Using YOLOv8m

Shivam Kumar[1], Nishant Kumar[1], Saloni Kumari[1], Anish Rudra[2] and Bappaditya Das[1]

[1]Department of Computer Science & Engineering, Dr. B. C. Roy Engineering College, Durgapur 713206, INDIA
Email Id: shivamkumarlkr000@gmail.com, nishant.si123@gmail.com, salonikumari3083@gmail.com
[2]Department of Information Technology, Dr. B. C. Roy Engineering College, Durgapur 713206, INDIA
Email Id: rudrabolpur2018@gmail.com

ABSTRACT

The early detection of plant diseases is crucial for preventing crop losses and ensuring agricultural sustainability. This study explores the application of YOLOv8m (You Only Look Once, version 8 medium), a state-of-the-art deep learning object detection algorithm, for image classification and disease detection in coffee leaves. The Coffee Leaf Disease Dataset, which includes annotated and unannotated images of healthy and diseased coffee leaves affected by conditions like rust and miner infestations, is used to evaluate YOLOv8's performance. YOLOv8's anchor-free architecture and real-time detection capabilities make it ideal for this task, offering high validation accuracy (91.4%) and F1-confidence score (0.96) in detecting disease-specific lesions. The model demonstrates significant improvements in both speed and precision compared to traditional approaches. This research highlights the potential of YOLOv8 in agricultural disease management and underscores its value in real-time disease detection applications in precision farming.

Keyword: Coffee leaf disease detection, real time image, YOLOv8m

I. INTRODUCTION

Coffee cultivation is a vital agricultural industry in India, benefiting both the economy and the livelihoods of millions of farmers. India ranks among the foremost coffee producers worldwide, with Karnataka, Kerala, and Tamil Nadu in the forefront of cultivation. The nation predominantly cultivates Arabica and Robusta varietals, essential for both internal consumption and export markets. The Coffee Board of India states that coffee farming sustains around 1.5 million farmers and is vital for rural development by generating jobs and promoting economic stability in coffee-producing areas (Coffee Board of India, 2023)

However, it faces significant challenges due to various diseases that can significantly impact yield. Quantifying the exact yield loss due to these diseases is challenging, as it can vary depending on factors like regional climate, cultivar susceptibility, and disease severity. However, studies have shown that coffee diseases can cause significant yield reductions, often ranging from 10% to 30% or more in affected areas. Here are some of the most common diseases affecting coffee production in India:

Daun Bercak, or leaf spot, is a prevalent disease in coffee plants caused by fungi like Cercospora and Colletotrichum. It is characterized by dark lesions on leaves, often with yellow halos. Severe infections lead to significant leaf drop, impairing photosynthesis and ultimately reducing coffee yield. Therefore, effective management strategies are essential for maintaining plant health.

Daun Karat, known as coffee leaf rust, is a highly destructive disease primarily caused by the fungus Hemileia vastatrix. It is marked by yellow-orange pustules on leaf undersides. As the disease advances, it leads to discoloration and early leaf drop, severely affecting photosynthesis. Consequently, this results in diminished yields and lower coffee quality, necessitating effective control measures by growers.

Conversely, Daun Sehat denotes healthy coffee leaves that are dark green and structurally robust, devoid of lesions. These leaves are crucial for the coffee plant's health, facilitating optimal photosynthesis and nutrient uptake. Healthy foliage enhances fruit development and improves coffee bean quality. Thus, regular monitoring and sound agricultural practices are vital for successful coffee cultivation.

Figure 1: Sample representative of each class

The timely recognition and accurate diagnosis of diseases permit farmers to adopt targeted strategies for minimizing crop loss [1][2]. Preserving crop productivity averts economic losses and defends global food security [3]. Traditional disease identification techniques, such as visual inspection and laboratory tests, are time-consuming, require expert knowledge, and require more scalability for large-scale applications [4][5]. Even with advancements in automated leaf disease detection methods for groundnut, several limitations still need to be addressed in current techniques.

The utilization of the YOLO (You Only Look Once) algorithm for detecting coffee leaf disease represents an innovative strategy within agricultural technology. YOLO, recognized for its real-time object detection abilities, can be effectively employed to identify and classify diseases in coffee leaves, facilitating timely intervention and management. This analysis examines into the incorporation of YOLO for detecting diseases in coffee leaves, highlighting its benefits and the obstacles encountered during its application.

YOLO is well-known for its capability to execute real-time object detection, an essential feature for agricultural applications where prompt disease identification can avert extensive crop damage. The algorithm segments images into grids, predicting bounding boxes and class probabilities for each cell, facilitating rapid and effective disease detection [6] [7].

Enhancements to the traditional YOLO model, such as the incorporation of attention mechanisms, have been proposed to improve its performance in detecting leaf diseases. By focusing on regions of interest within the leaf, these models can better distinguish between healthy and diseased areas, thereby increasing detection accuracy.

Although the main emphasis is on coffee beans, the application of YOLO for defect detection highlights its possible relevance to coffee leaves. The system demonstrated a remarkable accuracy of 95.11% in detecting defects, highlighting the effectiveness of YOLO in agricultural applications [8].

II. MATERIALS AND METHODOLOGY

A. Dataset

This dataset consists of 3000 images of coffee leaves affected by three common diseases: Sehat, Bercak, and Karat. The images were collected from Roboflow and manually annotated using LabelImg. Each class contains 1000 images. The images are in JPEG format with an average resolution of 1024x768 pixels. Image preprocessing techniques are applied to enhance image quality and standardize dimensions, followed by the division of the dataset into training, and validation (80:20) subsets to facilitate effective model training and evaluation. Data augmentation techniques, including rotation and flipping, were applied to increase dataset diversity.

B. Method

The training process employs the YOLOv8m architecture, incorporating data augmentation strategies to mitigate overfitting and enhance model generalization. Hyperparameters are meticulously tuned during training, and model performance is iteratively assessed using the validation set, focusing on minimizing detection errors. After the completion of the training phase, the model's efficacy is evaluated on the testing set, employing metrics such as precision, recall, and F1-score to quantify its performance. The final trained model is then deployed for real-time leaf disease detection, offering practical solutions for agricultural practitioners to monitor and manage crop health, thereby contributing to improved agricultural productivity and sustainability. We employed the Google Colab platform, a widely-used cloud-based environment for machine learning research, to conduct our tests. This platform granted access to a GPU, markedly expediting the training and inference procedures.

 ISSN NO: 2395-0730

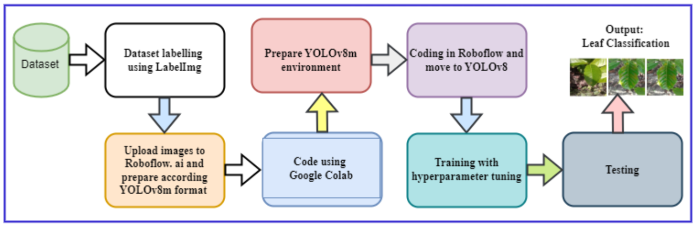

Figure 2: Proposed methodology of our study

III. RESULTS AND DISCCUSION

To investigate the impact of hyperparameter settings on model performance, we conducted experiments with varying batch sizes (16 and 32) and a fixed learning rate of 0.001. Our findings indicate that altering the batch size did not yield significant improvements in validation accuracy. Additionally, increasing the number of training epochs from 25 to 50 resulted in a slight enhancement in performance, suggesting that the model benefited from additional training iterations. Figures 3, 4, and 5 illustrate the confusion matrix, F1-confidence curve, and various loss functions generated in our experiments.

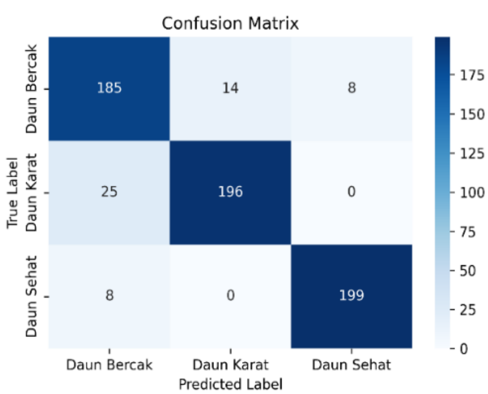

Figure 3: Confusion matrix

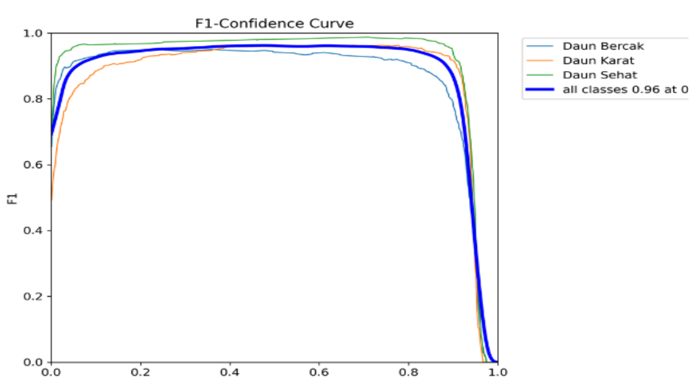

Figure 4: F1- confidence curve

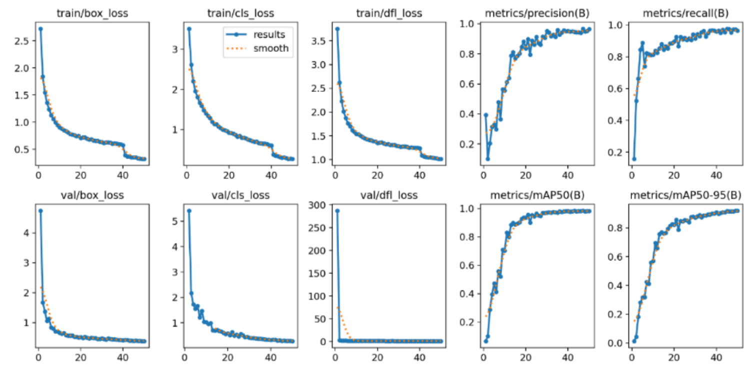

Figure 5: Different losses

The presented confusion matrix depicts the classification efficacy of a model designed to differentiate among three leaf disease categories: "Daun Bercak" (spotted leaf), "Daun Karat" (rusty leaf), and "Daun Sehat" (healthy leaf). The diagonal elements denote the quantity of accurately categorized cases for each class. For example, 185 "Daun Bercak" specimens were precisely identified as such. Off-diagonal elements signify misclassifications. Fourteen "Daun Bercak" samples were erroneously categorized as "Daun Karat." The analysis of the confusion matrix indicates that the model demonstrates robust performance in classifying "Daun Karat" and "Daun Sehat," with elevated accuracy rates. Nonetheless, it exhibits challenges in distinguishing between "Daun Bercak" and "Daun Karat," as indicated by the comparatively elevated off-diagonal values in these cells.

The model attained an overall accuracy of roughly 91.4%, indicating its competence in categorizing leaf types. The accuracy, along with the continual reduction in training and validation losses (including box, classification, and focus losses), signifies good model learning. Furthermore, notable enhancements in precision, recall, and mean average precision (MAP) metrics throughout training indicate improved accuracy and resilience in object detection and localization. The results indicate that the model has converged, demonstrating commendable performance in both classification and object identification tasks.

IV. CONCLUSION

Based on our experimental findings, we conclude that the model's performance is significantly influenced by the number of training epochs, with a notable improvement observed when increasing epochs from 25 to 50. While varying batch sizes did not yield substantial changes in validation accuracy, the model's overall performance demonstrates a promising ability to accurately classify leaf disease categories. The observed improvements in precision, recall, and MAP metrics further validate the model's effectiveness in object detection and localization. These results collectively suggest that the model has reached a satisfactory level of convergence, effectively addressing the task of leaf disease classification. Future research could explore the impact of different learning rates, optimizers, and data augmentation techniques to potentially further enhance the model's performance.

REFERENCES

[1] Tanti, Kumar Satyam, Gupta, Meenu, Kumar, Rakesh, and Obaid, Ahmed J. "Identification of Plant Leaf Disease using Image Augmentation and Deep Learning." In 2024 3rd International Conference on Computational Modelling, Simulation and Optimization (ICCMSO), 88-94, 2024.

[2] Saha, Soumyabrata, DasGupta, Suparna, Banerjee, Annwesha, Sarkar, Sayani, Ghorai, Sajal, Roy, Shreosa, Sarkar, Niloy, and Islam, Riyaz. "Deep Learning-Based Approach for Plant Disease Classification." In International Conference on Data Science and Applications,227–242. 2023. Springer.

[3] Ghildiyal, Ashutosh, Tomar, Mihir, Sharma, Shubham, and Dubey, Sanjay Kumar. "Plant Disease Detection and Classification Using Artificial Intelligence Approach." In International Conference on Soft Computing and Signal Processing, 165–175. 2023. Springer.

[4] Jafar, Abbas, Bibi, Nabila, Naqvi, Rizwan Ali, Sadeghi Niaraki, Abolghasem, and Jeong, Daesik. "Revolutionizing agriculture with artificial intelligence: plant disease detection methods, applications, and their limitations." Frontiers in Plant Science 15 (2024): 1356260. Frontiers Media SA.

[5] Chatterjee, Sourav, Dasgupta, Sudakshina, and Bhattacharya, Indrajit. "Leaf-Based Plant Disease Detection Using Intelligent Techniques—A Comprehensive Survey." In International Conference on Frontiers in Computing and Systems, 81–90. 2022. Springer.

[6] Shah, Nasim Banu, Ashutosh Gupta, and Arun Kumar. "Performance Analysis of Real-Time Object Detection algorithm for a Multi-Class Plant Disease Detection and Classification Using Deep Learning." *2023 11th International Conference on Emerging Trends in Engineering & Technology-Signal and Information Processing (ICETET-SIP)*. IEEE, 2023.

[7] Amritraj, Shoibam, Nitish Hans, and C. Pretty Diana Cyril. "An Automated and Fine-Tuned Image Detection and Classification System for Plant Leaf Diseases." *2023 International Conference on Recent Advances in Electrical, Electronics, Ubiquitous Communication, and Computational Intelligence (RAEEUCCI)*. IEEE, 2023.

[8] Luis, Vince Amiel M., Marc Vincent T. Quiñones, and Analyn N. Yumang. "Classification of Defects in Robusta Green Coffee Beans Using YOLO." *2022 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAIET)*. IEEE, 2022.