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YOLOv8-Based SUNet: Coffee Leaf Disease Detection Using a Hybrid Deep Learning Model

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Abstract—This paper presents a YOLOv8-based deep learning approach for detecting and classifying diseases in coffee plants, including Brown Eye, Leaf Rust, Leaf Miner, and Red Spider Mite. These diseases significantly affect yield and quality, making early detection essential. YOLOv8, known for its speed and accuracy, processes coffee leaf images to rapidly identify symptoms and classify them into disease categories. The model, trained on a diverse dataset, performs robustly across different environments. Due to its lightweight drones, enabling real time disease identification. architecture, it can be deployed on mobile devices and Experimental results indicate high precision, recall, and efficiency, surpassing traditional methods. Implementing this model can help farmers reduce crop losses, improve coffee quality, and minimize pesticide dependence, offering a scalable solution for disease monitoring in plantations.

Keywords: YOLOv8, Coffee Leaf Disease Detection,SUNet, Real-Time Object Detection.

INTRODUCTION

Coffee is one of the most consumed beverages globally and plays a vital role in agricultural economies. However, coffee plants are vulnerable to diseases such as Brown Eye, Leaf Rust, Leaf Miner, and Red Spider Mite, which significantly impact yield, quality, and market value. Traditional disease detection methods rely on manual inspection, which is time-consuming and inefficient, especially for large-scale plantations.

This project introduces YOLOv8**(**You Only Look Once**)**, a cutting-edge deep learning model for automated real-time disease detection in coffee leaves. By leveraging computer vision and AI, YOLOv8 enables precise identification**,** localization**,** and classification of disease symptoms, allowing farmers to take timely action, reduce pesticide dependency, and enhance sustainability. The proposed system supports mobile and drone-based deployment, making it a practical and scalable solution for modern coffee farming. Additionally, YOLOv8's ability to process images quickly ensures efficient disease monitoring, reducing crop losses and improving coffee quality. Its integration with advanced techniques like transfer learning and data augmentation enhances detection accuracy across diverse environmental conditions.

EASE OF USE

A. Ease of Deployment and Accessibility:

The YOLOv8-Based SUNet model is designed for seamless integration into real-world applications. Its lightweight architecture allows deployment on mobile devices and drones, enabling real-time disease detection in coffee plantations. The model processes images quickly, making it accessible for farmers, researchers, and agricultural workers without requiring deep technical expertise.

B. Accuracy and Efficiency in Disease Detection: By combining YOLOv8's object detection with SUNet's segmentation, the model achieves high precision in identifying and localizing coffee leaf diseases such as Brown Eye, Leaf Rust, Leaf Miner, and Red Spider Mite. This automated approach minimizes human error, reduces reliance on manual inspection, and improves agricultural sustainability by reducing pesticide dependency and enhancing

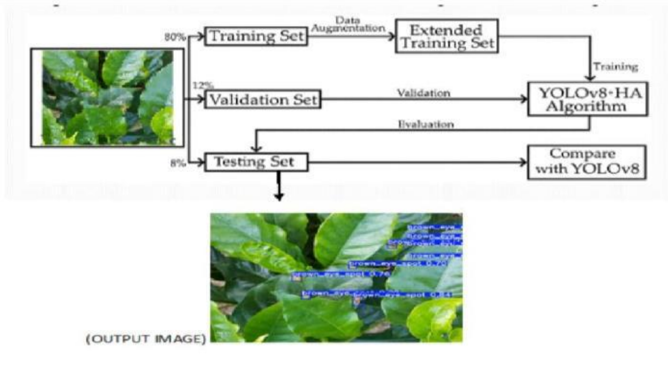

Fig: System architecture of proposed model

EXISTING SYSTEM

Current approach uses an advanced deep learning and computer vision approach for detecting and classifying coffee leaf diseases. The model integrates U-Net and SegNet for semantic segmentation, ensuring effective feature extraction and mapping. VGG16 is used to extract deep features, while a decoder with skip connections preserves spatial details for accurate reconstruction. Additionally, Mask R-CNN enables precise localization of diseased spots, and a pyramid pooling module captures multi-scale contextual information to enhance detection accuracy. Trained on JMuBEN and JMuBEN2 datasets, this hybrid model offers a robust, efficient solution for realworld agricultural applications, improving disease identification and optimizing coffee production.

LIMITATIONS

1. High Computational Complexity – Deep learning models need substantial computing power, making them resource- intensive and costly to train.
2. Limited Real-Time Application – High processing demands restrict real-time execution, making deployment on low- powered devices difficult.
3. Overfitting Risk – Overfitting occurs when a model memorizes training data instead of learning patterns, reducing accuracy on new data.

Several factors, such as computational complexity, realtime execution limitations, and overfitting risks, can significantly impact the performance and scalability of deep learning models, making optimization crucial for effective deployment in real-world applications.

PROPOSED SYSTEM

This project utilizes YOLOv8, a cutting-edge deep learning model, for real-time detection and classification of coffee leaf diseases such as Brown Eye, Leaf Rust, Leaf Miner, and Red Spider Mite. Unlike traditional methods, YOLOv8 provides simultaneous disease detection and localization with higher accuracy, faster processing, and lower computational cost. Designed for deployment on mobile devices, drones, and edge systems, it integrates data augmentation, transfer learning, and hybrid deep learning techniques for robust performance. The system ensures precise identification of disease severity, enabling more efficient interventions while minimizing the use of harmful pesticides, contributing to sustainable coffee farming.

TECHNIQUE/ALGORITHM USED

- YOLOv8 is the latest version in the YOLO series, designed for high-accuracy, real-time object detection with superior generalization capabilities.
- Improved backbones and neck structures enhance detection capabilities, allowing better recognition of small objects and disease symptoms on plant leaves.
- Supports edge devices, enabling on-field disease detection for farmers by analysing visual patterns like colour, texture, and shape, improving crop health monitoring.

This enables:

- real-time, precise coffee leaf disease detection
- supports efficient on-field deployment via mobile and drones.

A. ADVANTAGES

- Improved detection precision compared to earlier versions.
- Efficiency in Small Datasets.
- Optimized for deployment on edge devices.
- Detects small and overlapping objects effectively.

B. PROCESS INVOLVED

1. Data Collection – Gather images of healthy and diseased coffee leaves from various sources and annotate disease regions.
2. Preprocessing – Clean and enhance images through resizing, normalization, augmentation, and contrast improvement.
3. Model Selection – Choose YOLOv8 for its real-time object detection capability and efficiency.
4. Model Training – Train YOLOv8 on the dataset with hyperparameter tuning, loss optimization, and regularization techniques.
5 Model Evaluation – Assess detection accuracy using metrics like precision, recall, F1-score, and IoU.
6. Model Optimization – Improve speed and efficiency using techniques like quantization, pruning, and model distillation.
7. Prediction/Detection – Deploy the optimized model to classify and localize diseases on coffee leaves in real time. 8.Deployment & Integration – Implement the model on portable devices with a user-friendly interface for farmers and agricultural experts.

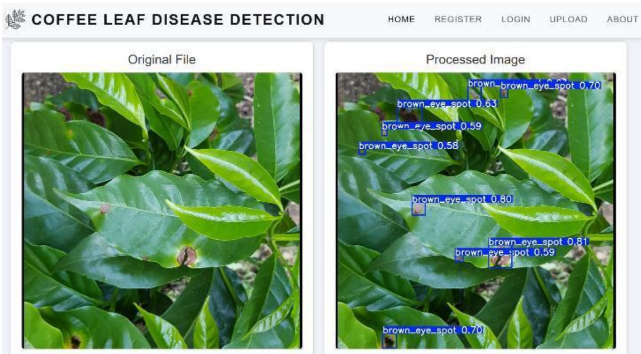

Fig: Coffee Leaf Disease Detection using YOLOv8

CONCLUSION

The proposed coffee leaf disease detection system using YOLOv8 provides a highly accurate and efficient solution for real-time identification of diseases like Brown Eye, Leaf Rust, Leaf Miner, and Red Spider Mite. By leveraging deep learning, it ensures fast processing speeds and compatibility with resource-constrained devices, making it ideal for field use. Early disease detection enables farmers to reduce crop loss and minimize chemical intervention. Future enhancements, including multispectral imaging, disease prediction, IoT integration, and a mobile application, will further improve usability. The system aims to empower farmers with an innovative, cost-effective, and sustainable approach to improving crop yield and quality.

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