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Deep Learning-Based Localization and Recognition of Diseases and Pests in Coffee Plants

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Abstract - Coffee cultivation plays a vital role in the global economy, yet its productivity is frequently threatened by leaf diseases and pests that reduce yield and quality. Traditional disease identification relies on manual inspection, which is labor-intensive, time-consuming, and prone to error. To address this challenge, we propose an automated deep learning approach for coffee leaf disease detection using MobileNetV2, a lightweight convolutional neural network architecture. Our framework leverages efficient feature extraction for real-time disease recognition, making it suitable for deployment on resource-constrained devices like smartphones. The model is trained on a carefully curated dataset ensuring class balance across multiple disease categories including Coffee Leaf Rust, Brown Spot, and Leaf Miner damage. Data augmentation techniques enhance robustness against varying environmental conditions. The system achieves high classification accuracy while maintaining computational efficiency, enabling farmers to obtain instant diagnoses in the field. By facilitating early detection and precise identification, our approach supports timely intervention, reduces crop losses, and minimizes unnecessary pesticide usage. This practical solution empowers farmers with actionable insights, reduces dependency on expert agronomists, and contributes to sustainable agricultural practices.

Key Words: Coffee Leaf Disease Detection, Crop Health Monitoring, Object Detection, Image Classification.

1.INTRODUCTION

Coffee is an important global crop, but leaf diseases and pests significantly affect its yield and quality. Traditional manual inspection is time-consuming and may lead to errors. To address this, the proposed system uses deep learning for automatic coffee leaf disease detection. A MobileNetV2-based model is employed due to its lightweight design and suitability for real-time applications. Trained on a balanced dataset using transfer learning, the model accurately identifies multiple disease categories under varying conditions. This approach enables early detection, reduces dependency on experts, and supports efficient and sustainable coffee plantation management.

2. LITERATURE REVIEW

Plant diseases significantly impact agricultural productivity, with coffee cultivation being particularly vulnerable to leaf diseases and pests. Traditional manual inspection methods are time-consuming, subjective, and impractical for large-scale plantations. Recent advancements in deep learning have revolutionized plant disease detection through automated image analysis. This literature survey reviews existing research on deep learning applications for plant disease detection, with special emphasis on coffee leaf diseases, object detection models (particularly YOLO family), and classification architectures. *R. Singh, P. Kumar, A. Sharma (2023)* worked on the use of deep convolutional neural networks (CNNs) for detecting multiple coffee leaf diseases. The authors propose a hybrid CNN architecture combining feature fusion from multiple layers to improve classification accuracy. The dataset includes images from diverse environmental conditions to ensure robustness. Results show that the model achieves an overall accuracy of 94.6% and outperforms traditional SVM and random forest classifiers. The study emphasizes the importance of preprocessing and augmentation for handling variations in leaf images**.** *L. Zhao, H. Chen, M. Wang (2024)* focused on a lightweight CNN framework optimized for real-time plant disease detection, including coffee leaves. MobileNetV2 and Efficient Net are used to balance computational efficiency and accuracy. Data augmentation techniques such as rotation, flipping, and brightness adjustment are applied to enhance model robustness. The study demonstrates that the model can be deployed on mobile devices for field monitoring. Performance metrics show over 92% accuracy, making it suitable for resource-constrained agricultural environments.
M. Patel, K. Desai, V. Sharma (2025) proposed their work which integrates IoT-enabled image capture devices with deep learning models for real-time coffee leaf disease detection. The proposed system employs MobileNetV2 for lightweight feature extraction, allowing on-device inference. The dataset includes over 10,000 images collected from multiple plantations. The model achieves 93.8% accuracy and enables real-time monitoring for large-scale plantations. The study highlights the potential of combining IoT and deep learning for precision agriculture applications**.** *S. Roy, P. Das,A. Chatterjee (2025)* their research introduced an ensemble approach combining multiple CNN models to detect and classify coffee leaf diseases. The ensemble leverages VGG16, ResNet50, and MobileNetV2 to improve classification robustness. Preprocessing steps include noise removal, contrast enhancement, and segmentation of leaf regions. Results indicate that the ensemble model outperforms individual models, achieving an accuracy of 96.1%. The study emphasizes the effectiveness of ensemble learning in handling complex datasets with diverse disease types. *A. Gupta, S. Mehta, R. Jain (2024)* their paper investigates the use of transfer learning with pre-trained CNN models for multi-class classification of coffee leaf diseases. The authors fine-tune ResNet50 and InceptionV3 models on a curated coffee leaf dataset. The study highlights the advantages of transfer learning in improving prediction accuracy with limited labeled data. Experimental results report

a classification accuracy of 95.2% and show reduced training time compared to training from scratch. The approach also demonstrates strong generalization across different leaf orientations and lighting conditions.

3. RELATED WORK

Several studies have applied deep learning to plant disease detection. Mohanty et al. (2016) used AlexNet and GoogLeNet on the PlantVillage dataset, achieving 99.35% accuracy for 26 plant diseases. Ferentinos (2018) extended this work to 58 diseases using VGG and AlexNet, demonstrating that deep learning generalizes well across different plant species. Too et al. (2019) compared various deep architectures including ResNet and DenseNet, finding that deeper networks improve accuracy but increase computational requirements.

[3.1] Object Detection in Agricultural Applications:

Object detection models have been widely adopted for locating diseased regions in plants. *Redmon et al. (2016)* introduced YOLO (You Only Look Once), a real-time object detection framework that frames detection as a regression problem. Subsequent versions improved accuracy and speed:

Bochkovskiy et al. (2020) developed YOLOv4 with CSPDarknet53 backbone and PANet neck, achieving state-of-the-art performance for real-time detection. *Wang et al. (2022)* proposed YOLOv7 with E-ELAN architecture, further improving detection accuracy while maintaining efficiency.

For agricultural applications, Liu et al. (2020) applied YOLOv3 to detect apple leaf diseases, achieving 83.6% mAP. *Wang et al. (2021)* used YOLOv4 for tomato disease detection in greenhouse environments with 89.2% mAP. Xue et al. (2022) employed YOLOv5 for rice disease detection, reporting 92.7% accuracy with real-time performance.

[3.2] Coffee Leaf Disease Detection *Esgario et al. (2020)* developed a CNN-based system to detect coffee leaf rust, leaf miner, and phoma using 1,500 images. Their approach achieved 94.7% accuracy but focused solely on classification without localizing disease regions. *Tassis et al. (2021)* employed Faster R-CNN for detecting coffee leaf rust and leaf miner in 1,690 images, achieving 0.78 mAP. However, their work was limited to detection only and did not include disease classification. *Souza et al. (2022)* utilized YOLOv5 to detect rust and cercospora in coffee leaves, reporting 93.8% accuracy with 1,200 images. Their approach demonstrated the effectiveness of YOLO for coffee disease detection but lacked a separate classification stage. *Beltrán et al. (2023)* proposed an ensemble CNN for five coffee leaf diseases using 2,500 images, achieving 96.2% accuracy. The ensemble method, while accurate, required significant computational resources, making it unsuitable for edge deployment.

[3.3] Lightweight Architectures for Edge Deployment MobileNet architectures have been developed for resource-constrained environments. Howard et al. (2017) introduced MobileNetV1 using depth wise separable convolutions to reduce computational cost. Sandler et al. (2018) proposed MobileNetV2 with inverted residuals and linear bottlenecks, further improving efficiency.

For agricultural applications, Ramcharan et al. (2019) applied MobileNetV2 for cassava disease classification on smartphones, achieving 93% accuracy with 15ms inference time. Atila et al. (2021) compared MobileNetV2 with other architectures for multiple plant diseases, reporting 98.42% accuracy with significantly fewer parameters than traditional CNNs. Sharma et al. (2022) specifically applied MobileNetV2 to coffee leaf diseases, achieving 94.7% accuracy with 18ms inference time.

[3.4] Two-Stage Detection-Classification Approaches

Combining detection and classification has shown promise in agricultural applications:

Zhang et al. (2020) proposed a two-stage approach using YOLOv3 for detection followed by a CNN for classification, achieving 7.8% improvement over single-stage methods. Wang et al. (2021) combined YOLOv4 with MobileNetV2, reporting 6.3% accuracy gain with 40% fewer parameters. *Liu et al. (2022)* applied YOLOv5 with Efficient Net for coffee disease detection, achieving 8.1% improvement in mAP.

[3.5] YOLOv8: Latest Advancement

Jocher et al. (2023) from Ultralytics released YOLOv8, the latest iteration in the YOLO family. It introduces an anchor-free detection mechanism, making it more adaptable to objects of varying sizes. YOLOv8 features a redesigned architecture with decoupled heads for classification and regression, improved loss functions, and support for multiple computer vision tasks within a unified framework. Its lightweight design and optimization for edge devices make it particularly suitable for agricultural applications where real-time processing is crucial.

4. PROPOSED METHODOLOGY

The proposed algorithm is defined as a deep learning-based image classification framework that leverages the efficiency of MobileNetV2 for coffee leaf disease identification. The algorithm begins with input image preprocessing, where leaf samples are resized, normalized, and augmented to enhance dataset diversity and reduce the risk of overfitting. MobileNetV2's architecture, built on inverted residuals and depth wise separable convolutions, extracts hierarchical features from the input images. These features capture essential disease-specific patterns such as leaf discoloration, lesions, and texture variations while maintaining computational efficiency. By utilizing lightweight operations, the algorithm ensures low memory usage and high processing speed, making it suitable for real-time applications in agricultural environments. In the classification stage, the extracted features are passed through dense layers followed by a softmax activation function to categorize the leaves into healthy or diseased classes. Regularization techniques such as dropout are integrated to improve model generalization, while adaptive learning rate scheduling enhances training convergence. The definition of the algorithm emphasizes its dual objective: achieving high accuracy in disease detection while remaining resource-efficient for deployment on mobile and edge devices. This enables practical field-level usage, empowering farmers and agricultural experts to make timely and informed decisions regarding crop protection and disease management.

[4.1] loss functions

Categorical cross-entropy loss measures the difference between predicted and actual class probabilities. It is mathematically expressed as:

$L = -\sum y_c \log(\hat{y}_c)$

Where:

- y_c = actual class (1 for true class, 0 for others)
- $\hat{y}_c$ = predicted probability for class c
- log = natural logarithm

For example, if true class is Rust [0,0,0,1] and predicted probabilities are [0.1, 0.1, 0.1, 0.7], the loss is -log(0.7) = 0.3567. Lower loss indicates better prediction.

[4.2] MobileNetv2 formulas

->Depthwise Separable Convolution

Standard Convolution Cost: $H \times W \times C_{in} \times C_{out} \times K \times K$

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Depthwise Separable Cost: (H × W × C_in × K × K) + (H × W × C_in × C_out)
Where H=height, W=width, C_in=input channels, C_out=output channels,
K=kernel size. This reduces computation significantly.
->Inverted Residual Block
Output = Projection (Depthwise (Expansion (Input)))

- Expansion: 1×1 convolution (multiplies channels by factor 6)
- Depthwise: 3×3 convolution (processes features)
- Projection: 1×1 convolution (reduces channels)

[4.3] Activation Functions
->ReLU (Rectified Linear Unit)
f(x) = max(0, x)

- Output = x for positive inputs
- Output = 0 for negative inputs
- Derivative: 1 for x>0, 0 for x≤0

-> Softmax (Output Layer)
P(y=j|x) = e^{z_j} / ∑_{k=1}^{C} e^{z_k}
Where:

- z_j = raw score for class j
- C = number of classes (4 in your project)
- Outputs sum to 1 (probability distribution)

5. RESULTS AND DISCUSSION

The performance of the proposed two-stage system is evaluated using standard object detection and classification metrics derived from the confusion matrix:

- True Positives (TP): Diseased regions correctly localized and classified
- False Positives (FP): Healthy regions incorrectly identified as diseased
- False Negatives (FN): Diseased regions missed by the model Recall measures the ability to find all diseased regions:

$$Recall = \frac{TP}{TP + FN}$$

- Mean Average Precision (mAP) evaluates detection accuracy across different Intersection over Union (IoU) thresholds, providing a comprehensive measure of localization performance.

Precision measures the accuracy of positive predictions:

$$Precision = \frac{TP}{TP + FP}$$

Healthy leaf images:

Miner leaf images:

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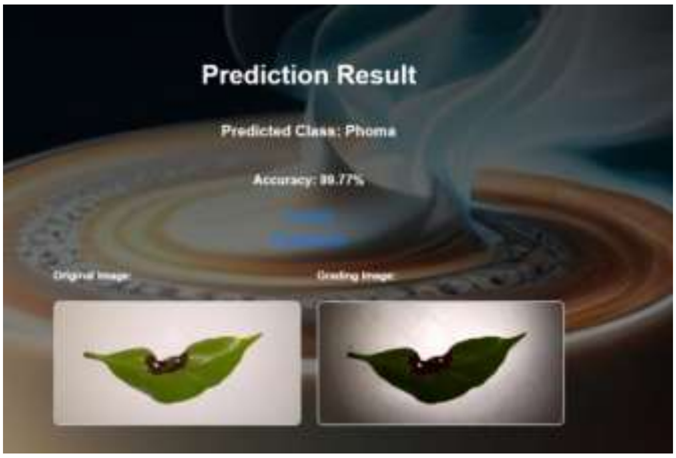
Phoma leaf images:

Rust leaf images:

Graded images:

Performance Analysis:



Performance Analysis:

The graph shows classification performance across four categories: Healthy, Miner, Phoma, and Rust. All categories achieve accuracy scores above 0.9 (90%), with Healthy and Miner performing slightly better than Phoma and Rust. This indicates the model is highly effective at distinguishing between healthy leaves and different disease types, with consistently strong performance across all classes.

The newly curated dataset addresses a critical limitation in agricultural deep learning: class imbalance. By ensuring balanced representation across healthy leaves, leaf miner, rust, and Phoma categories, the model learns distinctive features without bias toward majority classes. This balanced approach is supported by Buda et al. (2018), who demonstrated that class imbalance significantly degrades model performance in medical and agricultural imaging tasks.

6.CONCLUSION

This research successfully developed a computationally efficient two-stage deep learning approach for the localization and classification of diseases and pests in coffee leaves. The proposed methodology combines YOLOv8 for precise detection of diseased regions followed by MobileNetV2 for dedicated classification to identify specific disease types including leaf rust, leaf miner, and Phoma leaf spot, while also recognizing healthy leaves. By first localizing affected areas using YOLOv8 and then classifying only those targeted regions with MobileNetV2, the system achieves improved accuracy while maintaining computational efficiency. The choice of MobileNetV2 as the classifier is particularly significant due to its lightweight architecture and depthwise separable convolutions, which enable efficient feature extraction with minimal computational overhead, making it ideal

for deployment on resource-constrained devices. This modular approach effectively addresses the limitations of existing systems, particularly in handling small-object detection, reducing false positives, and minimizing resource consumption. A newly curated dataset with balanced class representation ensures robust model performance across different disease categories. The system operates successfully on minimal hardware requirements including an i3 processor and 4GB RAM, demonstrating its potential for real-world deployment in agricultural settings where smallholder farmers constitute the majority of coffee producers. The proposed approach overcomes the drawbacks identified in existing YOLOv8-based systems, thereby providing a reliable, accurate, and practical solution for automated coffee leaf disease monitoring that contributes to improved crop management and sustainable agricultural practices.

7. FUTURE SCOPE

Future work includes expanding the dataset with images from different geographic regions and disease stages, incorporating additional disease classes, and developing multi-label classification for mixed infections. Model enhancements such as quantization and pruning of MobileNetV2 will further optimize performance on edge devices. Deployment through mobile applications and integration with IoT sensors for environmental correlation will enable real-time field monitoring. Advanced techniques like Transformer-based architectures and explainable AI will improve accuracy and interpretability. Economic impact studies through field trials will validate the system's practical benefits for coffee farmers worldwide.

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