AI-Driven Approach for Digital Agriculture: A Case Study on Coffee Leaf Disease

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Abstract. *This study presents an AI-driven approach to coffee leaf disease classification by integrating deep learning and computer vision. Using DenseNet, MobileNet, and ResNet with transfer learning and data augmentation, the system achieved high accuracy, with DenseNet consistently performing the best. The experimental results highlight the influence of learning rate and class distribution on model performance. Model conversion ensures efficient deployment and supports real-time diagnosis. The proposed solution bridges AI research and practical agriculture, enhancing disease management while paving the way for scalable adaptive precision farming.*

1. Introduction

Coffee production plays a significant role in the economic and social development of over 50 countries where coffee is cultivated. Brazil is the largest producer, with 3.3 million tons and 2.25 million hectares dedicated to coffee production [CONAB 2024]. However, its productivity is continually threatened by plant diseases, such as coffee leaf rust, which is caused by the fungus *Hemileia vastatrix* Berkeley & Broome [Avelino et al. 2015][Silva 2018].

Coffee leaf rust is the main disease that affects arabica coffee production in Brazil and other coffee-growing countries. This disease causes yellow-orange spots on leaves, leading to leaf drop, reduced photosynthesis, and eventually lower coffee yields [Zambolim et al. 2024]. Timely and accurate diagnosis of these diseases is crucial for mitigating losses and implementing appropriate control measures [Silva 2018][Fones et al. 2020].

Traditional disease detection methods rely on manual visual inspection by agronomists, which, despite its effectiveness, is inherently time-consuming, subjective, and prone to human error. The scarcity of trained professionals, particularly in remote agricultural regions, further exacerbates this issue. Additionally, while laboratory-based foliar analysis provides more precise results, it remains inaccessible to a large number of smallholder farmers due to logistical and financial constraints [Ferraz 2021].

Despite advancements in agricultural technology, there is a need for scalable and automated solutions that enable real-time, accurate disease detection in coffee plants. Existing AI-driven approaches have demonstrated potential, but often rely on high-end computational resources, making them impractical for widespread adoption by farmers with limited access to technology. Furthermore, most studies focus on individual disease classification rather than providing a comprehensive, user-friendly diagnostic system suitable for field applications [Moreira et al. 2022, Albuquerque and Guedes 2024].

This paper aims to develop a mobile application that assists in the real-time recognition and diagnosis of coffee leaf diseases, leveraging Artificial Intelligence (AI) and Computer Vision techniques. Specifically, the research seeks to build a highly accurate AI model for detecting and classifying coffee leaf diseases using Deep Learning and an extensive dataset, design an intuitive mobile application for on-field diagnostics, and evaluate the system's computational efficiency and usability in resource-constrained environments. To address these challenges, this study proposes a novel AI-powered mobile application for the automated diagnosis of coffee leaf diseases. The main contributions of this paper are:

- Development of a Deep Learning-based Computer Vision model trained on an extensive dataset of coffee leaf images affected by multiple diseases.
- Integration of this model into a lightweight mobile application, enabling farmers to perform on-field disease diagnosis with minimal computational resources.
- A user-centric approach that provides real-time, actionable recommendations, bridging the gap between AI research and practical agricultural applications.

2. Related Work

[Aufar et al. 2023] proposed a web-based system for predicting Arabica coffee leaf diseases using different Convolutional Neural Networks (CNNs). They developed a web application diagnosed leaf health and provided suggestions for treatment. However, the proposed system is limited to a web-based application and lacks a mobile platform, which could enhance the accessibility and usability for field-based coffee disease diagnosis and management.

[Albuquerque and Guedes 2023] compared a traditional method, using Haralick features combined with Multilayer Perceptron (MLP), and a contemporary approach employing Deep Learning architectures, such as MobileNet, ShuffleNet, Inception, VGG, and EfficientNet. The experiments were conducted on the JMuBEN dataset, and a high classification performance was achieved using ShuffleNet. However, their approach did not incorporate data augmentation techniques, which could mitigate the class imbalance inherent in the dataset.

[Sharma et al. 2023] utilized transfer learning with CNNs, including VGG, MobileNet, ResNet and DenseNet, to identify coffee leaf diseases in a multiclass classification setup. They utilized data augmentation techniques, such as rotations and flips, to enhance dataset diversity and reduce overfitting. [Nawaz et al. 2024] proposed CoffeeNet, a deep learning model based on ResNet-50 integrated with a spatial-channel attention mechanism. The model achieved 98.54% accuracy on the multiclass classification.

[Saleki and Tahmoresnezhad 2024] proposed the Agry, a framework for plant disease classification leveraging pre-trained models such as EfficientNet with a spatial attention module and Support Vector Machine (SVM), achieving high classification performance. However, they carried out the classification using only two classes: healthy and diseased, where all coffee diseases are grouped into a single category. Although this approach reduces complexity, it may limit the model's ability to differentiate between specific diseases, which could be critical for targeted agricultural interventions.

[Yamakawa et al. 2024] applied CNNs with preprocessing techniques, such as Gaussian filters, Contrast Limited Adaptative Histogram Equalization (CLAHE), and Wavelet, for the multiclass classification of coffee leaf conditions. Despite achieving high classification performance, limitations include practical challenges with preprocessing filters in real-world scenarios and the computational cost of certain filters such as wavelets, which deliver suboptimal results with lower classification performance.

Although previous studies predominantly utilized CNNs, transfer learning, and preprocessing techniques, they were generally limited to web-based implementation in our centralized evaluations. By contrast, our approach leverages AI to ensure scalable, cloud-integrated disease diagnostics that enable continuous model optimization and real-time adaptation to evolving agricultural challenges. Table 1 summarizes the aforementioned approaches to coffee leaf disease classification, highlighting the AI strategies employed and their deployment platforms.

Table 1. Summary of AI strategies for coffee leaf disease classification.

Approach	Classification	AI Strategy	Mobile Application
[Aufar et al. 2023]	Multiclass	CNNs	○
[Albuquerque and Guedes 2023]	Multiclass	Haralick with MLP and CNNs	○
[Sharma et al. 2023]	Multiclass	CNNs with transfer learning and data augmentation	○
[Nawaz et al. 2024]	Multiclass	CNNs	○
[Saleki and Tahmoresnezhad 2024]	Binary	CNN with Spatial Attention Module and SVM	○
[Yamakawa et al. 2024]	Multiclass	CNNs and different preprocessing filters	○
Our Approach	**Multiclass and Binary**	**CNNs with transfer learning and data augmentation**	●

3. Material and Methods

The proposed method, summarized in Figure 1, employs an Artificial Intelligence as a Service (AIaaS) architecture for the automated analysis of coffee leaf images to detect and classify diseases. AIaaS provides a cloud-based solution that combines robust computational capabilities with advanced machine-learning frameworks, enabling efficient and scalable processing of agricultural data [Rodrigues Moreira et al. 2023, Rodrigues Moreira et al. 2024].

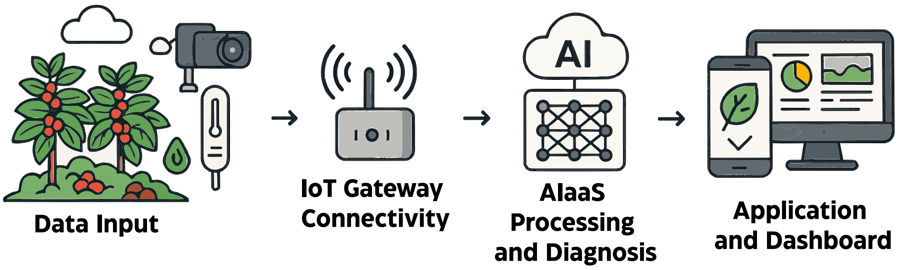
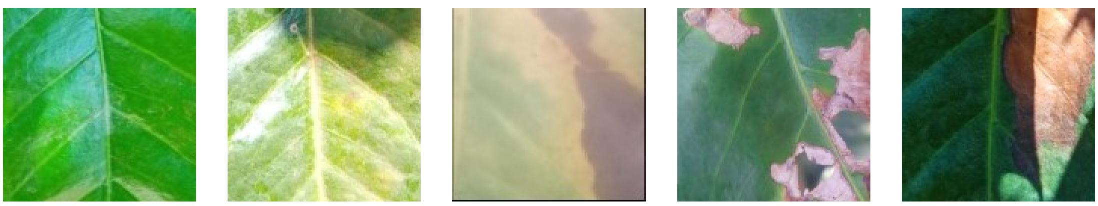


Figure 1. Proposed architecture scenario.

The input data utilized in this study originated from the JMuBEN and JMuBEN2 datasets [Jepkoech et al. 2021], which are publicly available and cover the health conditions of coffee leaves. Together, these datasets comprised 58,555 high-resolution images. Figure 2 presents representative examples of the five image classes analyzed in this study. A detailed description of each class and the respective number of images is provided as follows [de Carvalho 2013, Zambolim and Brenas 2018].

- **Healthy:** includes 18,985 images of coffee leaves with no visible symptoms, serving as a baseline for comparison.
- **Cercospora:** includes 7,682 images of leaves displaying symptoms of *Cercospora coffeicola*, commonly known as brown eye spot, which is characterized by circular brown lesions with yellow halos.
- **Leaf Rust:** representing 8,337 images, depicts leaves affected by *Hemileia vastatrix*, a fungal disease that produces characteristic orange spots on the undersides of the leaves, leading to premature defoliation.
- **Miner:** comprises 16,979 images of leaves damaged by *Leucoptera coffeella*, an insect pest whose larvae create mines or galleries within the leaves, thereby significantly reducing the photosynthetic area.
- **Phoma:** consists of 6,572 images showing the effects of *Phoma spp.*, a fungal pathogen that causes necrotic spots and dark lesions on leaves.



(a) Healthy (b) Cercospora (c) Leaf Rust (d) Miner (e) Phoma

Figure 2. Coffee leaf samples from JMuBEN dataset.

The images were divided into training and validation sets at a 70/30 ratio and processed on an RTX A4000 GPU. To ensure data quality and consistency, preprocessing steps included resizing images to 224×224 pixels, normalizing pixel values to facilitate training convergence, and applying data augmentation techniques, such as rotation and flipping, proposed by [Jepkoech et al. 2021] to enhance dataset variability and emphasize disease-affected areas.

Internet of Things (IoT) gateway serves as the central node for data acquisition and transmission. It collects environmental parameters and high-resolution images from sensors and cameras deployed in the field and transmits them efficiently to the AIaaS proposed by [Rodrigues Moreira et al. 2023]. This enables the management of the lifecycle of AI models, from training and optimization to deployment and monitoring, making it particularly suited for digital agriculture by enabling real-time analysis and insights for improved crop management. The AIaaS architecture outputs were integrated into an application dashboard for mobile applications that offered real-time visualizations of diagnostic results, classification metrics, and actionable recommendations.

In this study, CNNs were employed to detect coffee leaf diseases owing to their robust capability to automatically learn hierarchical features from image data [Ponti et al. 2017, Rodrigues Moreira et al. 2025]. DenseNet-161, ResNet-50, and MobileNet-V2 were selected for their complementary characteristics, and their capacity to capture intricate patterns makes them suitable for identifying the subtle disease characteristics of coffee leaves [Pacal et al. 2024].

DenseNet-161 leverages a densely connected architecture in which each layer is directly connected to every other layer, thereby promoting feature reuse and efficient gradient flow. This design reduces parameter redundancy, while enabling the model to learn complex patterns effectively [Huang et al. 2017]. ResNet-50 leverages deep residual learning, effectively mitigates the vanishing gradient problem and ensures efficient training for deeper networks [He et al. 2016]. MobileNet-V2 a lightweight model optimized for computational efficiency. Its depth-wise separable convolutions allowed for reduced memory and computational costs, making it ideal for scenarios requiring real-time inference or deployment on resource-constrained devices such as agricultural drones [Howard et al. 2017].

The evaluation of the CNNs was performed using: precision, recall, F1-score, and accuracy. These metrics were computed considering true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN), which are defined in Table 2.

Table 2. Evaluation metrics with definitions and examples.

Metric	Definition	Example
Precision = $\frac{TP}{TP+FP}$	Proportion of correctly predicted positive cases.	Of predicted diseased leaves, how many are truly diseased.
Recall = $\frac{TP}{TP+FN}$	Proportion of actual positive cases correctly identified.	Of diseased leaves, how many are correctly detected.
F1-Score $= 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$	Balance between precision and recall.	Combines precision and recall in one score.
Accuracy= $\frac{TP+TN}{TP+TN+FP+FN}$	Proportion of correct predictions overall.	Out of all leaves, how many were classified correctly.

4. Results and Discussion

The experiments were implemented using Python, leveraging the PyTorch framework for deep-learning model development and training [Paszke et al. 2017]. Additionally, a mobile application for coffee disease recognition was developed using React Native, enabling cross-platform compatibility and the seamless integration of real-time diagnostic functionalities.

All CNNs were trained using the backpropagation algorithm and Stochastic Gradient Descent (SGD) optimization, with training hyperparameters tuned to balance computational resources and dataset complexity. We conducted the experiments to analyze the performance of the AI models under different learning rates and class distributions. Specifically, the number of epochs was set to 10, with a batch size of 2, a momentum of 0.9, and learning rates of 1×10^{-4} and 1×10^{-3}. Once trained, the best model was integrated into a mobile application designed for real-time coffee disease recognition.

Multiclass Classification. DenseNet-161, MobileNet-V2, and ResNet-50 were evaluated using a learning rate of 1×10^{-4} (0.0001) for the classification of the five classes. The goal was to compare the effectiveness of the models and identify the most suitable architecture. Table 3 summarizes the results.

Table 3. Multiclass Classification Performance with Learning Rate 0.0001.

Model	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
DenseNet	**100**	**100**	**100**	**100**
MobileNet	99.08	99.04	99.04	99.06
ResNet	99.86	99.85	99.85	99.86

The results showed that all models achieved high classification performance, with DenseNet-161 reaching perfect classification (100% for all evaluation metrics). The minimal difference in performance among the models suggests that for this specific task and learning rate, the dataset features were well-defined, which likely enabled all three architectures to learn effective decision boundaries with minimal misclassification.

Subsequently, we conducted a new experiment, in which the models were trained using a learning rate of 1×10^{-3} (0.001), to evaluate the impact of this parameter on performance. The results, shown in Table 4, provide insights into how a higher learning rate affects the classification metrics.

Table 4. Multiclasss Classification with Learning Rate of 0.001.

Model	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
DenseNet	**100**	**100**	**100**	**100**
MobileNet	98.93	98.81	98.83	98.87
ResNet	99.21	99.15	99.15	99.18

While all models still exhibited strong results, a slight decrease in accuracy was observed for MobileNet and ResNet. This minor drop in performance could be attributed to the fact that a higher learning rate can sometimes lead to convergence instability. Although 1×10^{-3} is not excessively high, it may have caused small oscillations in weight updates, preventing the models from reaching their best possible performance. Interestingly, DenseNet maintained its perfect accuracy, suggesting that its architecture is more resilient to small variations in learning rate. These findings highlight that while deep learning models can be robust to certain hyperparameter changes, fine-tuning the learning rate remains crucial to optimizing performance for specific datasets.

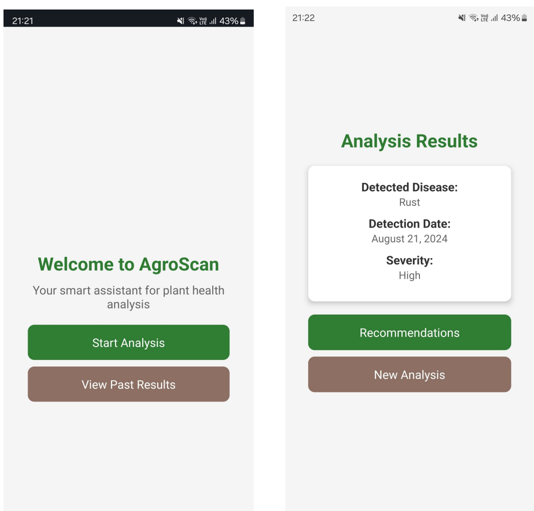
To enable efficient deployment on mobile devices, the trained models were converted to the Open Neural Network Exchange (ONNX) format, which allows the execution on resource-constrained devices, such as smartphones and embedded systems, reducing framework dependencies. The file sizes before and after conversion are as follows: DenseNet-161 retained a size of 111 MB, MobileNetV2 decreased slightly from 8.8 MB to 8.5 MB, and ResNet-50 reduced from 91 MB to 90 MB.

Binary Classification. This experiment focused on a binary classification task, selecting the two most representative classes from the dataset (healthy and miner). This scenario aimed to investigate the impact of class reduction on classification performance. Table 5 presents the evaluation results.

Table 5. Classification Performance considering Binary Classification.

Model	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
DenseNet	99.90	99.90	99.90	99.90
MobileNet	**100**	**100**	**100**	**100**
ResNet	**100**	**100**	**100**	**100**

In this experiment, the classification task was reduced to two classes while maintaining the same learning rate of 1×10^{-4}. The results show that all three models achieved high classification performance. This suggests that distinguishing between the two selected classes was a relatively simple task for the models, leading to highly confident predictions. Finally, Figure 3 shows the key screens of the mobile application, illustrating its coffee leaf disease-detection functionality.



(a) Home (b) Result

Figure 3. Main screens of the mobile application.

Comparison with Literature. We compared our best results with those of previous studies that utilized the same dataset to ensure a fair and consistent evaluation across methodologies, as summarized in Table 6.

Table 6. Comparison with state-of-the-art.

Approach	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
[Aufar et al. 2023]	100	100	100	100
[Albuquerque and Guedes 2023]	99.88	99.88	99.88	99.88
[Sharma et al. 2023]	100	100	100	100
[Nawaz et al. 2024]	97.10	96.68	96.89	98.54
[Saleki and Tahmoresnezhad 2024]	100	100	100	100
[Yamakawa et al. 2024]	98.25	98.00	98.00	98.00
Our Approach	**100**	**100**	**100**	**100**

While earlier studies explored various CNN architectures, preprocessing techniques, and traditional feature-based approaches, our method achieved a performance equal to or superior to the highest reported results in the literature.

5. Conclusion

The development of a mobile application employing AI and Computer Vision techniques aims to enhance the productivity and quality of coffee farming through the identification and diagnosis of coffee leaf diseases. Utilizing Deep Learning, a robust model was created and trained on a diverse dataset of images to ensure effectiveness in detecting various conditions. Built with React Native technology, the app offers an intuitive and user-friendly interface, enabling users of all skill levels to capture images and receive accurate diagnoses.

Experimental results revealed that factors such as learning rate and the number of classes significantly influenced the performance of the tested models. The DenseNet, MobileNet, and ResNet architectures demonstrated solid results, with performance varying depending on training configurations. The conversion of models to the ONNX format was crucial for ensuring compatibility and efficiency, enabling deployment on mobile devices and broadening access to coffee disease diagnostics.

In future work we plan to evaluate the app's ability to deliver real-time diagnoses, allowing swift responses to diseases and mitigating their impacts on crop productivity. Additionally, the app will provide educational resources on coffee diseases, including symptoms, treatments, and preventive measures, empowering coffee farmers to make informed decisions for effective management of their plantations.

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