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Automated identification and classification of Coffee Leaf Diseases using a Deep Learning Approach

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Abstract

Coffee is regarded as the most consumed drink around the globe and has accounted for a major source of income in the regions where it is cultivated. To meet the coffee marketplace's requirements around the globe, cultivators must improve and analyze its cultivation and quality. Several factors, such as environmental changes and plant leaf diseases such as Miner, Rust, Phoma, and Cercospora are major hindrances to increasing the yield of coffee. These diseases often appear visually similar in their early stages, making accurate identification challenging using traditional methods. To overcome this issue, we developed a deep learning solution based on 2D Convolutional Neural Networks (2D-CNN) to automatically detect and classify these diseases from leaf images. Our dataset was compiled from three publicly available sources and enhanced through LAB color space transformation and Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve image clarity. We implemented a multi-stage classification approach, tailoring the CNN architecture and data augmentation strategies at each stage to maximize performance. The model achieved a remarkable 99.86% accuracy on the final test set, demonstrating its strong potential as a reliable and efficient tool for disease detection in real-world coffee farming scenarios.

Keywords

Coffee Leaf Diseases, Deep Learning, 2D-CNN, Image Classification, Data Augmentation, LAB Color Space, CLAHE, Multi-Stage Classification, Agricultural applications

Introduction

The production of coffee, the most extensively traded commodity in the tropics, is produced by up to 25 million household farmers, who together account for up to 80% of global production.

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According to stats reported up to 2021, Brazil was the largest exporter of coffee, with Indonesia and India in second, and third, respectively (Aufar et al., 2023). Moreover, studies indicate that Sumatra has produced the finest quality coffee yield (“ICO, Monthly coffee market report”). The improvement of the agriculture industry, including coffee production, can be very beneficial for a nation's economy (Chang & Huang, 2021). Many other countries around the globe have put extraordinary effort into the area of agriculture to boost both the quantity and quality of various plants, including coffee. It is impressive how Saudi Arabia's agriculture has developed recently, especially in Jazan, where huge deserts have been turned into farmland and numerous plants are being grown. Specifically, Jazan is famous for cultivating coffee plants that produce the finest Khoulani coffee, one of the highest-quality coffees in the globe. Besides, most of the coffee is produced in poor countries, where it is an important means of income and contributes significantly to worldwide export revenues. Coffee is among the most consumed beverages in the world and one of the tops frequently traded goods (Jaworska & Majchrzak, 2025), with a market that is constantly expanding due to increasing consumption in developing countries and its significant impact on specialized and modern products in established nations. However, the world's rapidly changing environment is bringing in several coffee plant diseases that are harming its production quality and quantity and, eventually, lowering revenue. The agricultural industry's reliance on people physically examining the spots to identify such diseases presents a greater obstacle to coffee plant disease diagnosis as this process highly relies on the availability of domain experts which slows down the detection procedure (Jepkoech, Mugo, Kenduiywo, & Too, 2021). Moreover, such manual examination of plants is vulnerable to errors. Therefore, there exists a demand to develop an effective and reliable automated approach capable of locating and differentiating among various infections of coffee plant leaves.

The Fourth Industrial Revolution (FIR), the turning point of modern technological advancement, is the period in which physical and digital mechanisms can be interconnected via using advanced methods like deep learning (DL), machine learning (ML), artificial intelligence (AI), and big data (Hoosain et al., 2020). Additionally, the FIR can boost production and expansion in several ways. Farming represents one of the industries undergoing scientific expansion and advancement, where innovations like AI, DL, and ML have an advantageous effect on agrarian expansion and manufacturing capacity (Ali et al., 2025; Habib, Alyahya, et al., 2022; Waqas et al., 2025). An emerging technique called “smart agriculture” combines cutting-edge methods for raising crop output while simultaneously boosting inputs to farming in an ecologically sound way. Today, it is possible to cut expenditures and mistakes to attain environmentally and financially equitable farming (Habib, Alyahya, et al., 2022). Recent years have seen several initiatives to employ AI to aid growers in precisely identifying illnesses and pests that harm the farming industry, as well as to assess the nature of signs of various plant infections. By imitating human thinking operations, AI aims to give computers an understanding resembling that of humans. It presents new information while allowing for investigation, acquiring knowledge, and resolving issues. AI can revolutionize agribusiness by enabling producers to generate more effective outcomes with less effort while also offering a wide range of extra advantages (Albahli & Nawaz, 2022). ML applications have significantly increased in AI research during the past few years, especially the latest generation of models called DL. Particularly, DL approaches have outperformed conventional ML technologies in several fields (Khan et al., 2024) due to their ability to effectively capture the structural information of a sample. In the previous few years, a variety of approaches have been employed to detect illnesses in plants, and DL techniques have been regarded as highly effective. Due to the promising performance of various DL methods in agriculture, several investigations have been carried out, proving that image-based evaluation is trustworthy for recognizing various types of plant disorders (Habib, Khan, et al., 2022). Many researchers have utilized various DL models like convolutional neural networks (CNN) for diagnosing various types of plant infections, including coffee plant leaf abnormalities. CNNs are among the most promising DL-based strategies for autonomously discerning characteristics and effective model tuning, which employ numerous convolutional layers to encode various key learning points depending on suspected samples (Albattah et al., 2022).

Vast volumes of pictorial samples are required for network modeling in DL, which is a downside (Ayikpa et al., 2022). For instance, if there are fewer visuals in the databases, CNN's classification results suffer. Usually, transfer learning is employed to overcome this crucial limitation by offering several benefits, among them is that it doesn't need a lot of samples for network tuning because prior acquired knowledge from related activities can be applied to the present one. Although significant works have been introduced for the timely recognition of coffee plant leaves, there is much room for improvement. Although many works have employed the concept of applying object detection methods for locating and differentiating several types of plant leaf infections, little attention is paid to the employment of such approaches for recognizing the diseases of coffee plants. Further, historic approaches are not very competent to perform well for unseen cases and lack generalization ability. Moreover, approaches lack the ability to diagnose numerous coffee plant infections or to identify multiple occurrences of an abnormality on a single image (Aladhadh et al., 2022). Further, the extensive resemblance in the structural information of various illnesses complicates the classification task. The digital samples are subject to various types of distortions as well like containing light variations, clutter, blurring, color, and angle alterations which also introduce a challenge to the effective determination of the diseased plant leaf portions. There also exists a huge variation in the size of both coffee plant leaves and associated infected portions which is also a major challenge to this field.

Agricultural losses can be kept under control by quickly identifying the coffee plant leaf viruses and allowing the fast choice of the appropriate preventive measure. It also represents the first and most important step in avoiding such infections. Our goal is to design an approach that can properly locate and categorize coffee plant leaf illnesses. An earlier diagnosis of such infections can lead to more curative measures and longer survival times. Therefore, an effort is put into the present work to address the above-mentioned problems of coffee plant leaf abnormality recognition by suggesting an improved DL method called CoffeeNet. We have proposed an improved CenterNet approach by introducing an enhanced keypoints estimation ResNet-50 framework with an attention mechanism to extract reliable and precise features of various coffee plant leaf disorders. The redesigned feature extractor base enhances the model's capacity to collect significant sample information in the context of complex backdrops and unpredictable environmental constraints. The proposed approach effectively operates in real-world conditions while concurrently performing identification and categorization utilizing an end-to-end training strategy. The significant contributions to the proposed methodology can be outlined as follows:

We introduced a novel model called CoffeeNet with enhanced keypoints extraction CNN backbone for reliable identification and classification of coffee plant leaf syndromes.

A spatial and channel attention strategy is proposed in the feature engineering stage that computes inter-channel associations and pixels incorporations to nominate exact diseased regions of examined images with complex environment settings.

Improved determination of both diseased areas and associated classes of coffee plant leaves because of the better recognition capability of the proposed work.

A computationally efficient approach is suggested to recognize the various coffee plant leaf disorders as CenterNet utilizes a one-step object recognition strategy.

We accomplished a vast assessment of the introduced method on a complex and publicly accessible dataset to show the robustness of our model. The attained model performance in terms of both numeric scores and pictorial representation ensures the improved results of our work even in complicated background settings like noise, blur attacks, alterations of lighting, and other sample distortions.

Our remaining manuscript follows the following section arrangement: Section 2 comprises the methodology, while the dataset is discussed in Section 3. The proposed approach is explained in Section 4. Section 5 evaluates the performance, Section 6 contains the result discussion, and the conclusion is explained in Section 7.

Methodology

Figure 1 briefly illustrates the proposed methodology for detecting and classifying Arabica coffee leaf diseases. The system combines LAB color space transformation and CLAHE image enhancement with a 2D Convolutional Neural Network (2D-CNN), improving subtle color and texture features to enable more accurate and reliable disease identification. Coffee leaf disease involved sequential stages: data preparation, image transformation, model training, and evaluation. Stage-specific 2D-CNN models were trained using tailored datasets (Stage 1, 2, and 3), with unique layer settings and targeted data augmentation at each level. This stage-wise approach enhanced the model's ability to detect subtle variations in leaf features, improving accuracy and robustness across both binary and multiclass classifications.

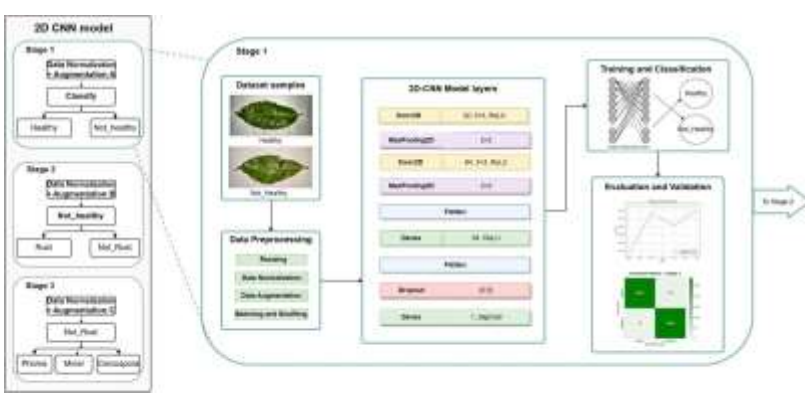

Figure 1. Block Diagram of First Stage of CNN Model

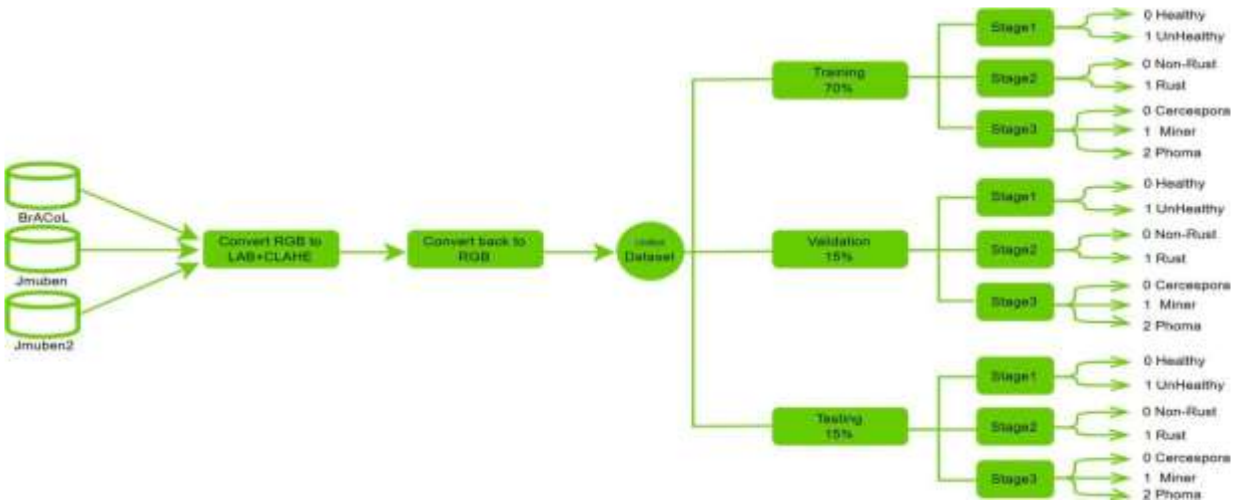

Figure 2. The architecture of the dataset used for our proposed model

Dataset

In this stage, we created a custom dataset by merging three sources: BrACoL (Krohling et al., 2019), JMuBEN (Jepkoech, Kenduiywo, Mugo, & Chebet, 2021), and JMuBEN2 (Jepkoech, Mugo, Kenduiywo, & Chebet, 2021). This dataset was prepared for training and evaluating our deep learning model, following several key steps illustrated in Figure 2. The aim of these datasets is to support the training and evaluation of deep learning models for identifying and classifying diseases in Arabica coffee leaves as shown in Figure 3.

JMuBEN (Jepkoech et al., 2021)

JMuBEN2 (Jepkoech et al., 2021)

BrACoL (Krohling et al., 2019)

Figure 3. Samples of datasets used to evaluate the diseases

Workflow Block Diagram

Figure 4 illustrates the workflow block diagram of the proposed methodology for classifying diseases in Arabica coffee leaves. The primary goal of this model is to enable researchers and farmers to detect leaf diseases efficiently using advanced image analysis and neural network techniques. The workflow is structured into the following key steps:

Image Dataset

Images will be sourced from three primary databases: JMuBEN, JMuBEN2, and BrACoL. These datasets include a diverse collection of images featuring both healthy coffee leaves and leaves affected by different types of diseases.

Preprocessing

At this stage, the images are preprocessed to ensure they are suitable for training the model. The following steps are involved:

- **Resizing:** All images are resized to a fixed width and height to maintain consistency and ensure compatibility with the model input requirements.
- **Normalization:** Pixel values are scaled from the standard 0–255 range to a smaller range (typically 0–1). This accelerates training and improves model performance by standardizing the input data.
- **Data Augmentation:** Applied only during the training phase, this step enhances dataset diversity without requiring new data. Techniques such as rotation, cropping, resizing, and color shifting are used to help the model generalize better and reduce overfitting.
- **Batching:** The dataset is divided into smaller batches so the model can be trained on one batch at a time. This improves memory efficiency and speeds up the training process.
- **Shuffling:** The training data is randomly reordered to prevent the model from learning any unintended patterns based on the sequence of the data.
- **Color Space Conversion and Enhancement:** Images are converted from RGB to LAB color space to separate luminance from chromaticity. CLAHE (Contrast Limited Adaptive Histogram Equalization) is then applied to the luminance channel to enhance visual features. The images are then converted back to RGB for model compatibility.
- **Manual Classification:** Each image is labeled into one of several categories—healthy, rust, phoma, cercospora, insect damage, or unhealthy—to train the model to distinguish among various leaf conditions.
- **Data Cleaning:** In the final step, the dataset is reviewed to remove duplicates, blurry or low-quality images, and incorrect labels. Images are then renamed and organized into folders based on their correct categories to streamline loading during model training.

Split Data

The dataset is divided into three subsets to ensure effective model training and evaluation:

- **Training Set (70%):** Used to train the model by allowing it to learn patterns from input images and their corresponding disease labels.
- **Validation Set (15%):** Used during training to fine-tune hyperparameters such as learning rate and network architecture. This helps monitor the model's performance and prevent overfitting by ensuring it generalizes beyond the training data.

- **Testing Set (15%):** Used after training to assess the model's final performance and evaluate its accuracy and generalization capability on unseen data. This partitioning strategy ensures the model not only learns effectively but also performs reliably on real-time data.

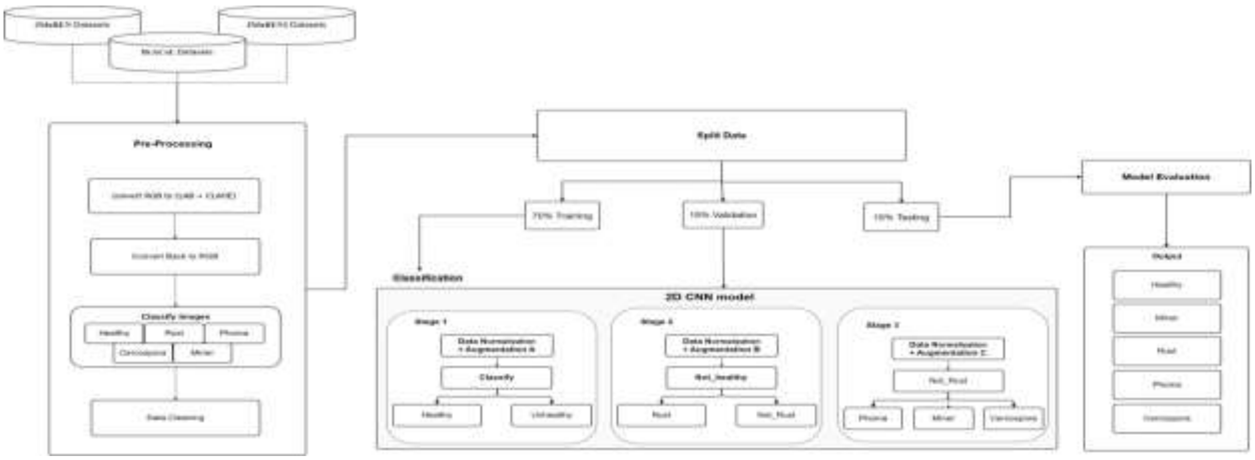

Figure 4. Workflow diagram for Coffee Leaf Disease Detection Using 2-CNN

CNN Model

At this stage, a 2D Convolutional Neural Network (2D-CNN) is used to extract features and recognize patterns in preprocessed coffee leaf images enhanced via the LAB color model and CLAHE. The training data is split into three subsets: each tailored with specific augmentation techniques and CNN layers to suit the classification task at that stage. This approach improves generalization and enables accurate identification of various coffee leaf diseases.

Performance Evaluation

After training and testing, the model’s performance is evaluated using metrics such as accuracy, precision, and error rate to assess its effectiveness in correctly classifying coffee leaf diseases.

Output Model

This final stage involves analyzing the processed images to diagnose coffee leaf diseases, to provide accurate insights into the plant's health condition.

Evaluation Performance

The performance of the 2D-CNN model for detecting coffee leaf diseases is evaluated using a confusion matrix, which is particularly suited for multi-class, multi-label classification tasks like this one. The model aims to classify images such as Healthy, Rust, Miner, or Spot. The confusion matrix helps illustrate how well the model distinguishes between these disease types.

Correct predictions are reflected in True Positives (TP) and True Negatives (TN), while misclassifications are captured by False Positives (FP) and False Negatives (FN). These values highlight both the model's strengths and areas needing improvement. Based on the confusion matrix, additional performance metrics—Accuracy, Recall (Sensitivity), Precision, Specificity, and F1 Score—are calculated to provide a comprehensive evaluation of the model's effectiveness, as summarized in Table 1.

Table 1. Comprehensive summarized measurements models

Matrix	Formula	Definition
Accuracy	$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$	Measures the total number of correct classifications divided by the total number of cases.
Recall / Sensitivity	$Recall = \frac{TP}{TP + FN}$ or $\frac{\text{True Positive}}{\text{Actual Results}}$	Measures the total number of true positives divided by the total number of actual positives.
Precision	$Precision = \frac{TP}{TP + FP}$ or $\frac{\text{True Positive}}{\text{Predictive Results}}$	Measures the total number of true positives divided by the total number of predicted positives.
Specificity	$F1\ Score = \frac{TN}{TN + FP}$	Measures the total number of true negatives divided by the total number of predicted positives.
F1 Score	$F1\ Score = \frac{2 \times \text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}}$	A single metric that is the harmonic mean of precision and recall

Results and Discussion

The overall performance of the complete classification system was evaluated on a final test dataset—Final Test— created by combining test samples from all previous stages. This dataset included 5,000 images, with 1,000 randomly selected high-quality images from each class: Healthy, Rust, Miner, Phoma, and Cercospora. Only images meeting key quality criteria, such as clarity and resolution, were included to ensure a fair and representative evaluation. As shown in Table 2, the integrated model achieved an impressive test accuracy of 99.86%, with all key evaluation metrics precision, recall, and F1-score—approaching 1.00 across all five classes. This demonstrates the model's high reliability and consistency, even when classifying diverse disease types in a unified, single-stage evaluation.

Table 2. Final evaluation results for the integrated classification system

Class	Precision (%)	Recall (%)	F1-score (%)	Support
Healthy	100.0	100.0	100.0	1000
Rust	99.0	100.0	99.5	1000
Miner	100.0	99.0	99.5	1000
Phoma	100.0	99.0	99.5	1000

(Table 2 continued)

Cercospora	99.0	100.0	99.5	1000
Overall Accuracy			99.86	5000

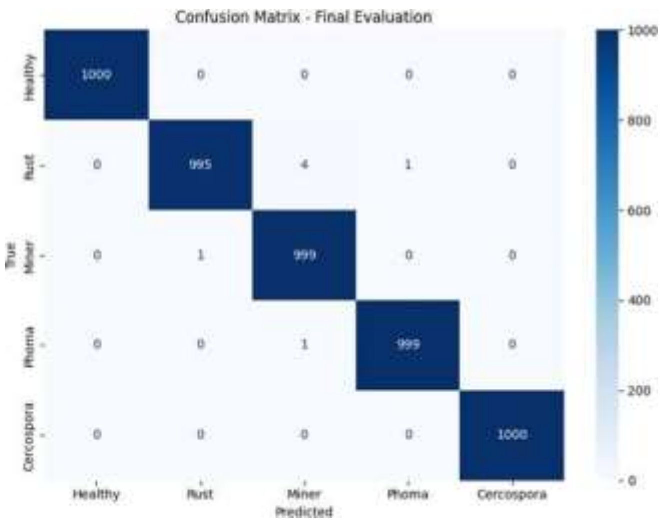

Figure 5. Confusion matrix of the integrated classification system

Further insights are illustrated in Figure 5, which presents the confusion matrix for the overall classification. The model correctly classified all 1,000 samples in the Healthy and Cercospora categories. For Rust, 995 out of 1,000 samples were accurately identified, with minimal misclassifications—four labeled as Miner and one as Phoma. Similarly, the Miner and Phoma classes each had only one misclassified image, highlighting the model's strong precision in distinguishing visually similar diseases.

These results confirm the robustness of the multi-stage classification strategy when integrated into a single, comprehensive model. The system's ability to generalize effectively from both binary and multiclass tasks underscores its potential for real-world agricultural diagnostics and plant disease monitoring.

Conclusion

This research developed a deep learning-based system for early detection of Arabica coffee leaf diseases using RGB images enhanced with LAB color space and CLAHE preprocessing. A custom 2D CNN architecture was designed and improved through a multi-stage classification approach after initial one-stage performance proved insufficient. A diverse dataset was created from multiple sources, and challenges like class imbalance were addressed through data augmentation and balancing. The final model demonstrated 99.86 accuracy and reliability, offering a strong foundation for future work in precision agriculture and early plant disease detection.

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