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# Deep Learning for Coffee Leaf Diseases Detection in Precision Agriculture

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## Abstract

Coffee production faces challenges like climate change, drought, and biodiversity loss. Sustainable systems can improve crop yields and quality, but also threaten ecosystem function. AI can help classify and identify coffee leaf diseases, but traditional machine-learning approaches struggle with big data. This study examines six deep learning models such as such as CNNs, ResNet50, MobileNet, GoogleNet, VGG16, and VGG19. The evaluation is done on the Kaggle dataset to classify between rust and miner diseases. MobileNet achieves superior results in terms of loss, accuracy, precision, recall, and F1-score with 0.0692, 0.973, 0.5625, 0.57143, 0.56693 respectively.

**Keywords:** Deep Learning; Coffee Leaf Disease; Sustainable Development; Precision Agriculture.

## 1 | Introduction

Coffee is a globally traded commodity, with Brazil, Vietnam, and Colombia being the largest producers. The growing market is driven by rising consumption in emerging economies and interest in specialty coffee. However, market imbalances and income distribution can threaten smallholder producers' livelihoods [1].

Coffee production, despite its strategic importance, faces considerable hurdles from climate change. Climate change is anticipated to reduce worldwide coffee output and coffee-suitable land by 2050, prompting immediate agronomic adjustments to reduce risks and assure long-term production sustainability. Other concerns include drought, salinity, biodiversity loss, suitability losses, changes in species seed availability, and stressor resistance [1]. Sustainable coffee systems may provide environmental benefits such as soil fertility, biodiversity, carbon sequestration, and pest control. However, environmental issues such as soil degradation, biodiversity protection, and pollution pose severe hazards to ecosystem function [2].

Precision agricultural (PA) technological improvements are critical to getting precise and reliable crop monitoring measurements. PA approaches can help an area grow crops with improved yields and quality at a lower cost. So, integrating artificial intelligence (AI) can help in automatic coffee leaf disease classification and identification. Traditional machine learning (ML) approaches such as support vector machines (SVM),

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random forest (RF), and decision trees (DT) are used widely for plant disease identification [3]. For example, Sahu and Pandey [4] introduced a hybrid RF multiclass SVM (HRF-MCSVM) strategy for detecting plant foliar diseases. Prior to classification, the image features are preprocessed and segmented by spatial fuzzy C-means to increase computational accuracy. The Plant Village dataset utilized contains 54,303 healthy and sick leaf pictures. Finally, performance indicators such as accuracy, F-measure, specificity, sensitivity, and recall value were used to assess the system's efficacy.

Although the ML learning approach is considered a more explainable AI approach, it faces some challenges in dealing with big and complicated data. Deep learning (DL) especially convolutional neural networks (CNNs) [5] consists of many convolutional (Conv) and pooling layers, followed by fully connected layers. The input layer of a CNN receives an image and passes information through Conv and pooling layers. Conv-layers use information like edges, corners, and textures to recognize objects. Pooling layers minimize spatial dimensions, increasing the model's generalizability. The output of the last pooling layer is flattened into a vector and routed via fully connected layers. These layers discover complicated patterns and correlations between features before creating the final prediction output [2].

Therefore, in our study, examine the performance of six DL models such as CNNs, ResNet50, MobileNet, GoogleNet, VGG16, and VGG19 in terms of loss, accuracy, precision, recall, and F1-score. The evaluation is done over the Kaggle dataset to classify between rust and miner diseases.

The rest of this paper is classified as follows: section 2 provides most coffee diseases and pests, section 3 shows the related work of this study, section 4 describes the methodology of our study, section 5 shows our proposed work, section 6 shows the results of the investigation, section 7 conclusion and future work.

## 2 | Coffee Diseases

This section aims to summarize the coffee disease that affects the world's production of coffee. Table 1 describes the most coffee pests and diseases. The table is classified into pest diseases, nursery diseases, and field diseases. The pest's disease is caused by insects that affect the crop. Nursery diseases are some diseases that can affect the seed of the crop. The field disease and disorder can affect leaves and berries [6].

**Table 1.** Coffee has different pests and diseases [6].

| Pests/diseases | | Symptoms |
|---|---|---|
| Insect pests | Green coffee scale | Green oval-shaped scales (2-3 mm) on leaf veins and tips of new shoots.<br>Sooty mold development.<br>Defoliation in severe cases. |
| | Aphids | Large numbers of small black aphids (2-3 mm) on new growth.<br>Associated with black sooty mold. |
| | Stemborers | Red stemborer: Red larvae tunneling in upper branches.<br>White stemborer: White larvae tunneling in the main stem and roots.<br>Wilting leaves, dead trees/branches, ringbarked trunks. |
| | Coffee berry borer | Fruit drop of young cherries.<br>Small holes in cherries.<br>Damaged beans. |
| | Mealybug | White waxy colonies on leaves, stems, and roots.<br>Associated with sooty mould. |
| | Leaf miner | Transparent areas in leaves.<br>Larvae on the underside of leaves.<br>Leaves distorted |
| Nursery diseases | Termites | Infestations in dead wood of older coffee and shade trees.<br>Wilting and dieback. |
| | Damping-off | The rapid die-off of seedlings.<br>Soft, rotten stems. |

| | | |
|---|---|---|
| Nursery / field diseases | Cercospora leaf spot | Brown spots with reddish margins on leaves.<br>Spots on both leaf surfaces.<br>Leaves appear burnt when severe. |
| Field diseases and disorders | Coffee leaf rust | Pale yellow spots on leaf undersides.<br>Spots become powdery and yellow to orange.<br>Leaf drop, leading to dieback and berry loss. |
| | Sooty mould | Leaves covered with black, powdery soot.<br>Grows on honeydew from scale and other sucking insects. |
| | Anthracnose | Twig dieback, brown blight on cherries, leaf necrosis.<br>Brown sunken lesions on cherries and leaves. |
| | Overbearing dieback | Severe leaf loss, branch dieback, premature ripening, hard and black cherries.<br>Alternating heavy and poor crops. |

## 3 | Related Work

In this section, we introduce some contributions that identify and classify coffee leaf diseases using different techniques which are summarized in Table 2.

**Table 2.** Summarization of Coffee leaf disease classification studies using DL and ML.

| Ref. | Year | ML | DL | Accuracy |
|---|---|---|---|---|
| **[7]** | 2024 | | ✓ | 99.78% |
| **[8]** | 2023 | | ✓ | 98% ,96% |
| **[9]** | 2024 | | ✓ | 98.54 |
| **[10]** | 2023 | ✓ | | 98.95% |
| **[11]** | 2023 | | ✓ | 97.9% |
| **[12]** | 2023 | ✓ | | 97.5% |
| **[13]** | 2024 | ✓ | | 84% |
| **[14]** | 2023 | | ✓ | 99.8% |
| **[15]** | 2023 | | ✓ | 98.57% |

Yang et al. [7] introduced a nondestructive, and high-throughput approach for classifying coffee provenance using mass spectrometry (MS) analysis and intelligence algorithms. Volatile components in coffee fragrance were identified using self-aspiration corona discharge ionization mass spectrometry (SACDI-MS), and the resulting MS data were processed using a bespoke DL algorithm to automatically conduct origin verification. To enable high-throughput analysis, an air curtain sampling device was developed and integrated with SACDI-MS to avoid volatile mixing and signal overlap. Coffee samples from six sources were classified with an accuracy of 99.78% at a throughput of 1 s per sample.

Yamashita and Leite [8] proposed an approach based on CNNs in a low-cost microcontroller board that can classify coffee leaf disease in situ, without the requirement for an internet connection. Early detection of disease in coffee farms is critical for productivity and product quality. Two datasets were used, in addition to images obtained with the development board itself, for a total of almost 6000 images of six distinct disorders. When implemented, the proposed architectures (cascade and single stage) achieved accuracy values of roughly 98% and 96%, respectively, proving their capacity to aid in the identification of diseases in coffee plantations, particularly those maintained by farmers with limited resources.

Nawaz et al. [9] presented an effective DL model known as the CoffeeNet. Explicitly, an enhanced CenterNet technique is provided by using a spatial-channel attention strategy-based ResNet-50 model to compute deep and disease-specific sample features, which are subsequently categorized using the CenterNet framework's 1-step detector. We examined the localization and cataloging results of the proposed technique on the Arabica coffee leaf repository, which comprises images acquired under more realistic and complex environmental limitations. The CoffeeNet model achieves a classification accuracy of 98.54% and a mAP of 0.97, demonstrating the effectiveness of our method in localizing and classifying various types of coffee plant leaf diseases.

Tasi et al. [10] provided a new approach for assessing single coffee beans using MS without sample preprocessing. The approach extracts the primary species using a solvent droplet combining methanol and deionized water, enabling rapid mass spectra extraction. The approach was tested on expensive palm civet coffee beans and shown to be very accurate, sensitive, and selective. The researchers also utilized a ML technique to identify coffee beans based on their mass spectra, attaining 99.58% accuracy, 98.75% sensitivity, and 100% selectivity during cross-validation. This method might assist in detecting low-cost coffee beans mingled with high-cost ones, helping both customers and the coffee industry.

Milke et al. [11] proposed a DL approach for automatically detecting coffee wilt disease. The study entailed gathering photos of healthy and diseased coffee, creating CNNs to identify between healthy and infected leaves, and optimizing the dataset for training and testing. The experiment employed 4000 photos of healthy and diseased coffee leaves, 80% for training and 20% for testing. The model grouped input images effectively, with a mean training accuracy of 98.1% and a mean test accuracy of 97.9%, utilizing a learning rate of 0.0001, a Sigmoid output layer activation function, 100 epochs, and an 8:2 training and testing dataset ratio.

Another contribution, by Ruttanadech et al. [12] aimed to classify near-infrared spectra for Aspergillus ochraceous infection in Robusta green coffee beans. Six learning methods were utilized: linear discriminant analysis, SVM, k-nearest neighbors, decision tree, Naive Bayes, and quadratic discriminant analysis. Four types of fungal contamination were discovered: non-fungal infected beans on days 1 and 3, and fungal contaminated beans on days 1 and 3. The Tree technique was discovered to be the most effective, with a training accuracy of 97.5% and a classification accuracy of 97.5%. This highlights the potential of NIR spectroscopy and machine learning for early identification of fungal infection in green coffee beans.

He et al. [13] gathered molecules with coffee odors and described their regularity, with the ultimate goal of developing a binary classifier that can detect whether a molecule has a coffee odor. In this investigation, 371 coffee-odor molecules and 9,700 non-coffee-odor molecules were gathered. The Knowledge-driven data was pre-trained using Graph Transformer (KPGT), support vector machine (SVM), random forest (RF), multi-layer perceptron (MLP), and message-passing neural networks (MPNN). The predictor was built around the model that performed the best. The KPGT model's prediction accuracy topped 0.84, and the predictor was deployed as a website named PredCoffee.

Abuhayi and Mossa [14] proposed a DL strategy for identifying and classifying coffee illnesses based on CNNs. This study is broken down into three stages: image preprocessing, feature extraction, and classification. Gaussian filtering and data augmentation techniques were used to strengthen the model and minimize noise. The CNNs were utilized to extract high-level features by combining GoogLeNet-based and RESNET-based architecture, which can capture more complex and meaningful characteristics of input images, such as shapes, objects, and patterns, and are useful for tasks like object recognition and classification. The collected characteristics were then categorized using multi-layer perceptrons (MLPs), ML, and ensemble classifiers. The suggested model outperformed other classifiers, with a testing accuracy of 99.08%.

Karthik et al. [15] presented a network that achieves exact classification by combining inception modules, a global context module, and a multi-head attention module. Inception modules extract features of several sizes and generate important feature maps at various abstraction levels. The Global Context Block generates a single feature vector using a channel attention mechanism, modulating input feature maps to provide high-level contextual information. The multi-head attention module detects complicated links between features and combines them to create a more powerful representation. The network beat prior networks in detecting coffee leaf disease, with an accuracy of 98.57% and an F1 score of 98.55%.

# 4 | Methodology

In this section, we provide some preliminaries of different DL architectures that were used in this study.

## 4.1 | Convolutional Neural Networks

The CNNs consist of three types of layers. The convolution (Conv) layer, is the main component of CNNs. The core computations are done in this layer. This layer conducts a dot product between two matrices, one representing the set of learnable parameters, often known as a kernel, and the other representing the limited section of the receptive field. The kernel is geographically smaller than a picture, but it is more detailed. This implies that if the picture consists of three (RGB) channels, the kernel height and width will be spatially limited, but the depth will stretch throughout all three channels.

The pooling layer substitutes the network output at specific points by calculating a summary statistic of neighboring outputs. This helps to reduce the spatial size of the representation, which reduces the amount of computation and weights needed. The pooling procedure is applied to each slice of the representation independently.

Finally, the fully connected layer (FC) where neurons exhibit a complete connection to all neurons in the preceding and following layers. The FC layer contributes to mapping the representation between the input and output.

## 4.2 | Residual Network

ResNet-50 is a complicated architecture that may extract complex features from huge datasets with fewer parameters, but it is computationally costly and hard to understand. ResNet-50 may also be unsuitable for some applications, such as NLP, due to its low ability to learn abstract characteristics [16].

## 4.3 | MobileNetV1 Architecture

MobileNetV1 is a computationally effective and precise model for smartphone applications with minimal datasets, making it suited for real-life situations due to its inverted residuals and linear bottlenecks. MobileNetV1 has scalability, accuracy, computing efficiency, and tuning limits, requiring further tuning for optimal performance in complicated tasks or datasets [17].

## 4.4 | GoogLeNet Architecture

GoogleNet is a type of CNN based on the Inception module to choose many Conv filters, hence boosting input image accuracy. However, it has a high computational cost, training challenges owing to multiple layers, and requires a huge amount of data. Furthermore, the complexity and lengthy inference time make it unsuitable for real-time applications [18].

## 4.5 | VGG Architecture Model

VGG is a popular approach for object identification, image segmentation, and facial identification, known for its excellent accuracy in identifying complicated patterns in images. VGG has drawbacks, such as the necessity for vast volumes of data for training and the computational expense of managing so many parameters [17].

# 5 | Coffee Leaf Diseases Identification using DL: Case Study

In this section, we compare the effectiveness of six DL models CNNs, ResNet-50, MobileNetV1, GoogleNet, VGG16, and VGG19. All models use Adam optimizer, batch_size = 20, epochs = 10, and Dropout (0.5). The data is divided into 80 Training and 20% testing. Figure 1 shows the general framework of Coffee leaf disease classification.

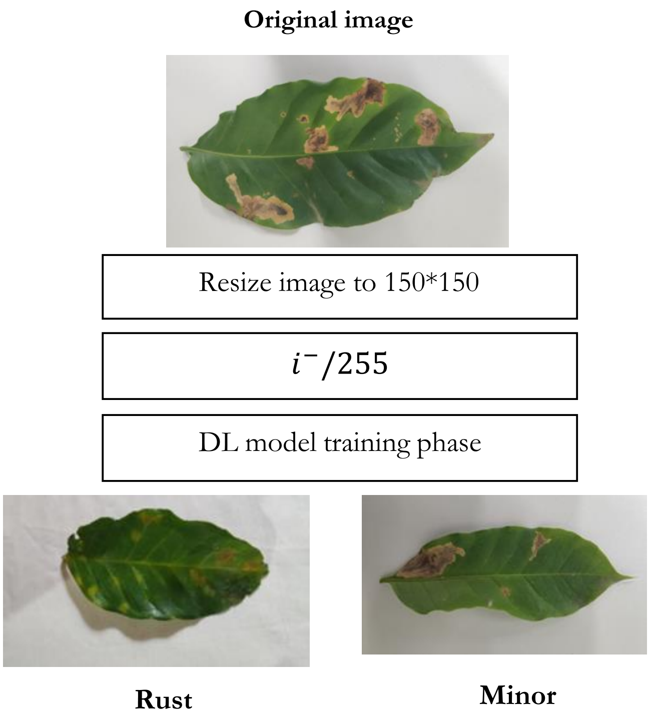


**Figure 1.** The general framework of DL models for coffee leaf disease classification.

# 6 | Result and Discussion

This section includes a coffee disease dataset description, evaluation metrics, and statistical analysis related to coffee disease classification.

## 6.1 | Dataset Description

The dataset was used in our research paper called "Artificial intelligence for detection and quantification of rust and leaf miner in coffee crop" from Kaggle, this dataset was proposed to detect Rust and Leaf Miner in coffee leaves. The dataset was manually collected and labeled the images from a farm in Brazil, totaling 285 images of the rust and 257 of the miners. The images are in the original captured resolution of 4000x2250 pixels. The data was collected using a simple smartphone camera to capture the images, and most parts of the photos were taken in a laboratory with a white background [19].

## 6.2 | Evaluation Metrics

Our proposed work was evaluated using accuracy, precision, recall, and F1-score. To display a confusion matrix of the proposed work, the following metrics can be computed:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{(\text{TP} + \text{FP} + \text{TN} + \text{FN})} \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \tag{3}$$

$$\text{F1} - \text{score} = 2 * \frac{\text{Precision} \cdot \text{Recall}}{(\text{Precision} + \text{Recal})} \tag{4}$$

Where TP, FN, TN, and FP represent the number of true positives, the number of false negatives, the number of true negatives, and the number of false positives, respectively

### 6.3 | Statistical Analysis

In this section, we provide the results of our investigation on six DL models CNNs, ResNet50, MobileNet, GoogleNet, VGG16, and VGG19 in terms of loss, accuracy, precision, recall, and F1-score. Table 3 shows the superior accuracy for MobileNet and smaller loss.

**Table 3.** Performance of different DL models for coffee leaf disease classification.

| Model | Loss | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|---|
| **CNNs** | 0.2317 | 0. 8868 | 0.5 | 0.39298 | 0.44008 |
| **ResNet50** | 0.3385 | 0.9042 | 0.53521 | 0.46914 | 0.49999 |
| **MobileNet** | 0.0692 | 0.973 | 0.5625 | 0.57143 | 0.56693 |
| **GoogleNet** | 0.1123 | 0.964 | 0.5873 | 0.5873 | 0.5873 |
| **VGG16** | 0.2873 | 0.8892 | 0.5862 | 0.53968 | 0.56198 |
| **VGG19** | 0.0860 | 0.955 | 0.66667 | 0.69841 | 0.68217 |

## 7 | Conclusion and Future Work

Due to global problems in the environment pollution and climate change. Plant leaf disease automatic detection and identification can achieve sustainable development goals. Coffee is one of the important crops that affected in the last years. In this context, our study aims to investigate the performance of several deep learning (DL) models for coffee leaf disease classification such as CNNs, ResNet50, MobileNet, GoogleNet, VGG16, and VGG19 in terms of loss, accuracy, precision, recall, and F1-score. MobileNet shows superior results with an accuracy of 97.3% and a loss of 0.0692.

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## Author Contribution

All authors contributed equally to this work.

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## Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

## Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

## Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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