A deep learning model for detection and classification of coffee-leaf diseases using the transfer-learning technique

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ABSTRACT

The early treatment and detection of plant diseases are important, as many diseases affecting crops are highly contagious. Recent advancements in deep learning have helped to provide innovative tools that have not only assisted early detection but also significantly improved the performance and accuracy of Coffee Leaf Disease (CLD) classification and treatment. However, training a deep learning model from scratch can be both resource and time-consuming. To overcome this challenge, the transfer learning technique can take full advantage of pre-trained models for more general tasks on extensive datasets to ameliorate the performance of a new, related task using few-shot training. This paper proposes a deep learning model, coupled with transfer learning, for CLD detection that aims to provide high-accuracy forecasting of diseases that could affect coffee leaves. Our method involves 195 different pre-trained deep learning models, including real-time models like MobileNet and dense ones like EfficientNet and ResNet, for detecting four different diseases. The findings suggest that the EfficientNetB0 model, with transfer learning, has the most relevant accuracy (99.99%), thus offering an effective solution for classifying coffee leaf diseases. This result could be used to develop applications that help coffee growers improve their crops' productivity and quality by detecting coffee plant leaf diseases early and accurately. Such an Artificial Intelligence-based application would provide growers with timely control measures, preventing the spread of disease and minimizing crop damage.

1. Introduction

Coffee is a highly significant agricultural commodity, valued at over 70 billion US dollars at retail [1]. It is the primary source of income for over 100 million people and is vital to the economies of over 60 countries [2]. Coffee is significant around the world for various reasons, involving social, economic, and cultural aspects across different regions. It has become a cultural symbol and is deeply embedded in the social fabric of many societies. In countries such as Saudi Arabia, it has evolved into a cultural icon wherever people gather for conversation, work, or leisure. The rising importance of coffee has led to increasing investment in coffee plantations.

Coffee plants are, however, susceptible to various diseases that may have a negative effect on the health and yield of crops, lowering revenue and affecting investment. Hemileia vastatrix, the pathogen that causes coffee rust, can impose annual losses on coffee investments of up to two billion US dollars [3]. It can also be a principal constraint on producing Arabica coffee (Coffea arabica) worldwide. The fungus Phoma affects coffee crops, resulting in multiple detrimental symptoms, including leaf lesions, branch desiccation, and the decay of flowers and fruits. Coffee leaf miners, also known as Leucoptera coffee, are deemed to be one of the most critical coffee pests due to the substantial damage they inflict on coffee plantations. Cercospora leaf spot, caused by Cercospora coffeicola, can cause leaf fall in seedlings and, in severe cases, stem dieback. When berries are infected, they ripen before the beans are mature, resulting in unpleasant flavors when the coffee is processed.

These Coffee Leaf Diseases (CLDs) and their impact on economies necessitate more effective detection methods to enable subsequent treatment by farmers. In fact, effective disease management in coffee plantations often involves a combination of cultural practices, chemical control (fungicides and pesticides), and the use of disease-resistant coffee varieties. Monitoring and early detection are crucial to implementing timely control measures and preventing the spread of diseases. Artificial intelligence applications are the most widely adopted and effective solutions. More specifically, using machine learning for automatic coffee disease detection is an innovative approach that can contribute significantly to the early diagnosis and effective deal with diseases in coffee plantations.

Machine learning has increasingly been used in recent years to identify plant leaf diseases [4]. Noteworthy advancements have been observed in plant disease recognition, thanks to the substantial performance improvements demonstrated by deep learning, a subset of machine learning [5]. Furthermore, recent research on CLD classification has successfully integrated deep learning into its methods, leading to significant improvements in both the accuracy and sensitivity of detection systems [6]–[9]. However, little has been done to employ these approaches in the diagnosis of coffee leaf diseases. The competence of earlier similar approaches has not been proven, and they have not been generalized. Further to this, the classification of coffee leaf diseases can be complicated due to the extensive resemblance in the structure of different illnesses [5].

With regard to the efficiency of Deep Learning (DL), it is acknowledged that DL models perform optimally when testing and training data share a similar feature space and distribution [10]. However, the challenge arises when there is a shift in distribution, requiring the rebuilding of models from scratch, which is costly. To overcome this limitation, the introduction of transfer learning has proven beneficial [10]–[12]. In traditional DL, the knowledge gained from past experiences is often ignored, and learning processes proceed without consideration of this prior knowledge. On the other hand, transfer learning incorporates previously learned tasks to process new ones. The integration of transfer learning techniques into deep learning methods offers new possibilities in terms of efficiency and generalization.

The main goal of this research is to forecast the kinds of illnesses that affect coffee leaves at an early stage. We adopted a deep learning model based on the transfer learning technique to achieve this goal. We aim to propose a practical, effective, and efficient solution that can be implemented in real-time or in laboratory contexts.

The following are the main contributions of this research:

- Applying several deep learning models, including ResNet50, MobileNet, and EfficientNetB0, as the classification backbones for the detection of coffee plant diseases.

- Based on transfer learning applied to Deep Learning models and MobileNet, the proposed method identifies and categorizes five different forms of CLD. These consist of leaves that are healthy as well as those that have Phoma, Cercospora, Rust, and Miner diseases.
- Making use of pre-trained models on huge databases and fine-tuning them for the CLD-specific tasks.
- Proposing an algorithm that includes several steps for the learning procedure.

The adoption of the transfer learning model provided several advantages. It reduces computing and training time by learning generic properties, like textures, edges, and simple shapes, from the pre-trained models. It also improved the classification of the diseases by changing the pre-trained classifiers.

Paper is organized as follow. Section 2 presents a brief summary of relevant publications on CLD categorization, which establishes the background for our investigation. Section 3 describes the Pre-trained CNN models we used, the transfer learning method we employed, and the details of our proposed CLD classification method. Section 4 presents the dataset used to evaluate our model, the configurations of different CNN models based on the transfer learning approach, and how we trained, validated, and evaluated this model. The last section concludes the paper and highlights the key findings.

2. Related Works

Deep learning is a machine learning sub-field based on ANNs (Artificial Neural Networks) to learn from different data types. Inspired by the human brain, artificial neural networks can learn complex patterns and extract knowledge from data. Training deep neural nets is a process of tuning their internal settings to gradually improve their ability to map inputs to outputs. Recent breakthroughs in both theoretical concepts and practical engineering have led to significant advances in this computationally intensive process [13]. When DL architectures demonstrated their performance and began to evolve over time, researchers employed them for image recognition and classification. These architectures have also been found to be applicable in various agricultural contexts [14], particularly for CLD detection [9]. The general process of CLD detection based on deep learning models is illustrated in Fig. 1.

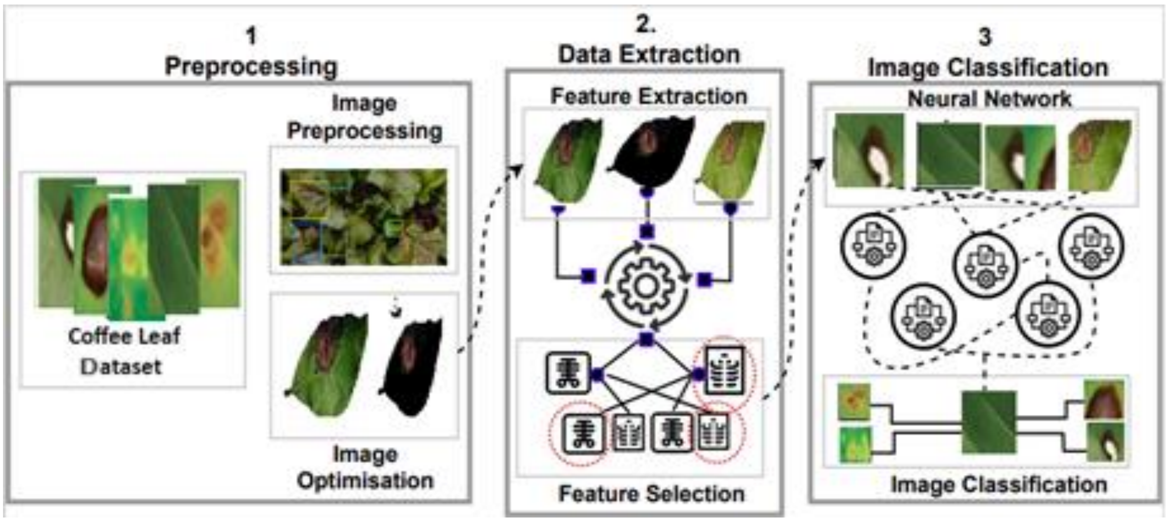

Fig. 1. General process of the CLD detection method using deep learning

Deep learning has outperformed other machine learning methods in multiple fields, including CLD classification [15]–[19]. In this context, Ayikpa et al. [15] evaluated a combination of machine learning and deep learning methods for CLD detection and classification. For machine learning, the models used were LR, KNN, SVM, RF, MPL Classifier, GNB, and DT Classifier. For deep learning, the models used were ResNet-50, MobileNet, DenseNet-201, VGG-19, InceptionV3, and a custom Convolutional Neural Network (CNN) model. These models were trained and evaluated on the JMuBEN dataset to classify and recognize CLD. They demonstrated good performance using deep learning models for the task of CLD classification.

Also, Montalbo et al. [20] proposed a method for separating Barako CLD into four classes: Healthy, Rust, Sooty Molds, and Cercospora Leaf Spots. The researchers employed three deep-learning models: Xception, VGG16, and ResNetV2-152. Their analysis revealed that the trained models achieved impressive classification accuracies, with VGG16 in the lead at 97%, followed by Xception at 95%, and ResNetV2-152 at 91%. As well as this, a study by Esgarioa et al. [9] evaluated common CNN architectures (AlexNet, GoogLeNet, VGG19, ResNet50) for multi-task learning, involving both severity estimation and classification of biotic stress. Among these, ResNet50 proved to be the most effective, achieving an average accuracy of 94.05% for stress classification and 84.76% for severity estimation. The authors of [16] proposed a CLD method and utilized five deep learning models for its implementation: ResNet, InceptionV3, DenseNet, Xception, and VGG16. They demonstrated that DenseNet emerged as the optimal choice for this image classification task. Another type of method of CLD recognition combines various deep learning models [18]. For example, [18] introduced an ensemble model that relies on two distinct deep neural networks to aggregate representations. The authors demonstrated that the proposed model enhances accuracy when compared to a single architecture. In evaluating the BARACOL dataset, the best results were noted when combining MobileNet and EfficientNet models. This models fusion reaches a precision, accuracy, and recall of 97.45%, 97.80%, and 97.92%, respectively.

Deep neural networks often outperform traditional algorithms and are excellent at classification tasks. However, training these powerful models can be time-consuming, especially for large datasets. Transfer learning offers a compelling solution, significantly reducing the time it takes to train neural networks and potentially even improving performance. So, to leverage the benefits of transfer learning, studies in the literature have incorporated this approach into their CLD classification methods. In [17], a CLD classification method using transfer learning and fine-tuning was proposed. The method classifies leaves into groups with three distinct diseases: Rust, Phoma, or Cercospora. The proposed models for this classification are based on the ResNet50, DenseNet121, and VGG19 architectures. These models underwent training with transfer learning and fine-tuning. Evaluation on the JMuBEN and JMuBEN2 datasets demonstrated the superiority of DenseNet, achieving an accuracy of 99.36% after fine-tuning the model. Other recent works have introduced transfer learning into their CLD classification methods, demonstrating its effectiveness in enhancing the results for pre-trained models [21]–[23]. Table 1 provides a comprehensive overview of recent methods for Coffee Leaf Disease (CLD) classification, selected based on strict inclusion and exclusion criteria. The inclusion criteria required that all articles be written in English and published as journal papers between 2020 and 2023. Moreover, the studies had to utilize a combination of Deep Learning and Transfer Learning techniques and specifically focus on datasets related to CLD.

Conversely, the exclusion criteria filtered out articles not meeting these standards. Papers not written in English, or published as conference papers, book chapters, or other non-journal types, were excluded. Studies published before 2020, those not employing Transfer Learning methods, or those using datasets unrelated to CLD, such as datasets focused on coffee beans, were also omitted from consideration. These criteria ensure a focused and relevant analysis of the most recent advancements in CLD classification.

Table 1. Comparative Analysis of Coffee Leaf Disease Recognition Methods

Reference	Year	Methodology	Dataset	Results	Weakness
Zhuang [20]	2020	VGG16 using transfer learning and fine-tuning	Private dataset: 4667 images	97%	Small dataset and detection of only 3 diseases
Wang et al [24]	2022	Few-shot learning-based MobileNetV2	Private dataset: 1685 images	96%	Small dataset
Yamashita and Leite [25]	2022	Ensemble architecture based on DL with three fine-tuned CNN (ResNet152, EfficientNetB0, VGG16)	Private dataset: 1300 images	97.31%	High complexity of the classification algorithm and a small dataset
Nawaz et al [26]	2022	MobileNetV2 using transfer learning	RoCole dataset: (1560 images) [27]	99.93%	Classification into two classes (healthy and unhealthy)
Javierto et al [28]	2022	ResNet50 using transfer learning	Private dataset: 1747 images	97.07%	Small dataset
Ahmad et al [29]	2022	MobileNet and ResNet using transfer learning	Private dataset: 1200 images	97.01% and 99.89%	Small dataset
Yebasse et al[16]	2023	DenseNet using transfer learning and fine-tuning	Private dataset: 37,939 images	99.57%	Detection of 3 diseases

It can be seen from Table 1 that existing work on CLD detection has usually been performed on a small dataset with just three disease types, which neglects several diseases that affect coffee leaves. Also the performances achieved could be further enhanced, especially with the effective use of the transfer learning technique. This assumption will be clearly explained in our proposed methodology.

Based on the literature, advances in agricultural technology, particularly in the realm of coffee-leaf disease detection studies, hold tremendous promise for revolutionizing crop management practices, enhancing disease prevention strategies, and ultimately improving agricultural sustainability and food security. Furthermore, integrating deep and machine learning processes with sensor data enables automated detection and classification of coffee leaf diseases. By training these algorithms on large datasets, including most CLD types, researchers can develop robust early disease detection models capable of identifying subtle disease symptoms and distinguishing between different disease types with high accuracy and at the earliest stages. These findings motivate our proposed method based on transfer learning for early CLD detection and efficient intervention.

3. Method

3.1. Transfer Learning

Training CNN models for classification tasks require large-volume data, extensive computation time, and powerful GPUs, making it very challenging to implement. Transfer learning is an ideal solution to addressing these challenges. Transfer learning uses a pre-trained model on a large source dataset to solve a new, related task (target domain). This approach improves efficiency compared to training a model from scratch by capitalizing on the learned features from the source task. In order to gain a deeper understanding of transfer learning, one can refer to a recent survey on the topic by [30]. In transfer learning, a pre-trained model is often used to build a new model focused on a specific task with different data, as shown in Fig 2. The newer model can resolve problems in few-shot learning. The objective behind this process is to share certain features across tasks. This is executed by using some of the standard features of the pre-trained model and developing new ones without the need to start from scratch. This eventually saves developers' time and ensures the creation of flawless and highly accurate models.

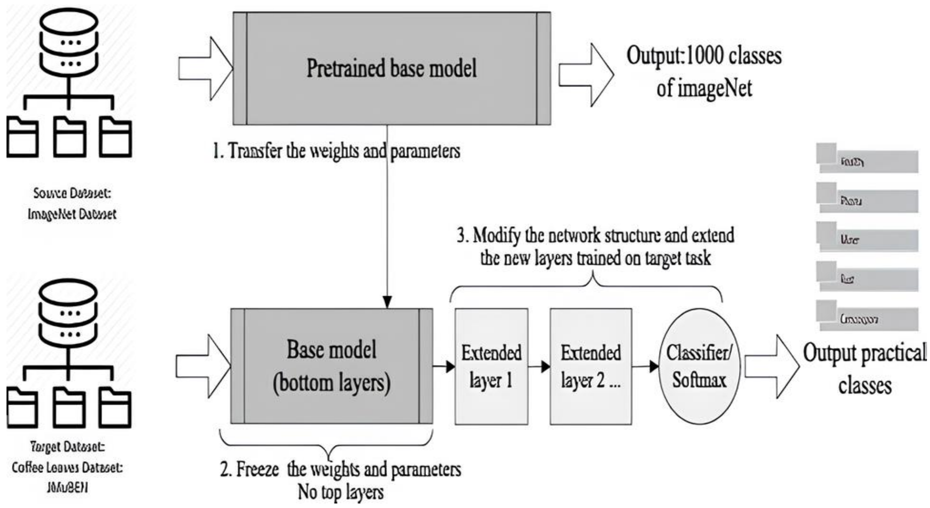

Fig. 2. Detailed architecture of the deep transfer learning based CLD classification method

In this study, the selected models are all pre-trained for image classification tasks on ImageNet, which is similar to our objective, although with different content. Hence, transfer learning is used as a domain adaptation process, given that the target and source applications are related but not exactly alike. Models trained on a source domain will be fine-tuned on a target domain, adapting the learned representations to the specific characteristics of the new data. Since the lower layers of deep neural networks are often responsible for learning generic features like edges, textures, and basic shapes, transfer learning allows them to use these learned features for our CLD-specific task, saving computation and resources when compared to starting from random weights. Furthermore, this adaptation permits effective feature extraction.

3.2. Proposed method

3.2.1. General overview

As explained in Section 3.1, transfer learning is a few-shot learning method that ensures better and faster results. In transfer, learning addresses several key issues. These include how to apply different methods to distinct source-target domains and how they bridge different transfer knowledge. Hence, a powerful transfer learning key question is how to adapt a pre-trained model to perform a new and seen task. A basic model that has been pre-trained on large datasets may frequently be simply fine-tuned to facilitate model adaptation or transfer learning, as these models have been shown to generalize better than ones that have been randomly initialized [8]. A common approach to accelerate training is to use pre-trained networks as a backbone for new tasks. This involves adding specialized functionality to these pre-trained models, such as object detection or recognition modules [8]. In this research, we adopt the second method and then freeze weights and parameters of the backbone models without the top layers (see Fig. 2)

The proposed method was based on transfer learning applied to deep learning models and MobileNet to detect and classify 5 types of CLD. These involved Healthy Leaves and leaves affected by, Cercospora spots, Phoma disease, Miner disease, and Rust disease. The proposed method consisted of leveraging pre-trained backbones on a large dataset and fine-tuning them for the CLD tasks. The proposed process included several steps, as explained below (see Algorithm 1).

Algorithm 1. The algorithm of our proposed method is based on the Transfer learning process

Require: backabone model, JMuBEN dataset

Ensure: New model adapted for CLD classification

Ensure: Height Accuracy and Few-Shot pseudo code

1- Load and Preprocess Image Data

Batch size: 16

Image size: (m, n)

▷ Image size needs to be adjusted related to the backbone model input Data augmentation: Random flips and rotations (horizontal and vertical, 0.2 rotation)

Image preprocessing: Normalization

2- Create Base Model

Base model: Freeze top layers

Pre-trained weights: ImageNet

3- Add Classification Head

Global average pooling layer

Dropout layer: Rate of 0.2

Final dense layer: 5 outputs (matching number of classes)

4- Compile Model

Optimizer: Adam

Learning rate: 0.0001

Loss function: Categorical crossentropy

Metrics: Accuracy

5- Train Model Initial epochs: 10

while epoch≤ 10 do: Early stopping: Monitor loss, the patience of 3 epochs

end while

6- Fine-Tune Model

Fine-tuning start layer: 100

Fine-tuning learning rate: 0.00001

Fine-tuning epochs: 5

7- Evaluate on Test Data

3.2.2. Selected Backbones models

Four pre-trained models (EfficientNetB0, ResNet50, MobiNetV1, and MobiNetV2) have been used in this work for feature extraction after applying transfer learning, as presented in Fig. 2. The selected models, in this study can be classified into two categories.

3.2.2.1. Dense Deep Learning Model

Some deep learning models can be large and computationally intensive, requiring substantial resources for training and inference. The complexity of these models often leads to higher accuracy, but deployment may be limited to resource-constrained devices.

- EfficientNetB0

  EfficientNetB0 is a convolutional neural network (CNN) architecture designed for image classification tasks and was introduced in the study of [10]. Unlike traditional CNNs that prioritize depth or width, EfficientNetB0 uses compound scaling. This means that depth, width, and resolution are scaled uniformly using fixed coefficients [10]. This approach optimizes the model for both accuracy and efficiency. With only 18 convolutional layers, EfficientNetB0 is the smallest version of the EfficientNet family [10]. Each layer uses kernel sizes of 3x3 or 5x5 for efficient feature extraction. The model progressively increases filters (W) in each layer while decreasing resolution. Without significantly increasing the computational cost, this strategy increases the feature complexity as the network progresses. In this way, EfficientNetB0 offers an attractive solution for image classification tasks, as it achieves a high level of accuracy with a relatively small and efficient architecture (see Fig. 3).

Fig. 3. Illustration of the EfficientNetB0 architecture

- ResNet50

  is a variation of the ResNet model, boasts a structure comprising 48 convolutional layers, complemented by 1 Average Pool layer and 1 MaxPool layer (see Fig. 4). As a convolutional neural network, ResNet50 delves 50 layers deep. Renowned as a backbone for various computer vision tasks, ResNet, or Residual Networks, marked a significant breakthrough in neural network design by enabling the training of exceptionally deep networks, surpassing 150 layers. This innovative neural network concept was introduced by He et al. [31].

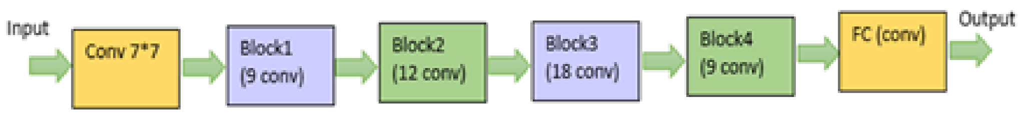

Fig. 4. Illustration of the Resnet50 architecture

3.2.2.2. Lightweight convolutional neural networks

MobileNets is a family of convolutional neural networks (CNNs). It is particularly suitable for use in mobile devices and other resource-constrained environments. MobileNets are not just limited to mobile devices. Their lightweight nature makes them applicable to various edge computing tasks with limited processing power. They can be used for image classification, object detection, and other computer vision applications on these devices.

- MobileNet-V1

  Due to its efficiency, it is a convolutional neural network (CNN) architecture specifically designed for mobile and embedded vision applications [32]. It achieves this by replacing the traditional convolution layers, which are computationally expensive, with depth-separable convolutions. Compared to a network using regular convolutions of equivalent depth, this substitution significantly reduces the number of parameters presented in Table. 2. Depth-separable convolutions divide the regular convolution process into two separate steps: the depth-wise convolution step and the pointwise convolution step. In the depth-wise convolution step, individual filters are applied to each input channel, performing a filtering operation on a per-channel basis. The pointwise convolution step then combines the depth convolution outputs using 1x1 convolution, creating new features. As a result, MobileNet-V1 makes use of separable depth convolution to achieve high performance in mobile and embedded vision tasks while maintaining a lightweight and efficient architecture.

Table 2. MobileNet-V1 Layers

Input	Operator	*t*	*c*	*n*	*s*
224^2 x 3	Conv2d	-	32	1	2
112^2 x 32	bottleneck	1	16	1	1
112^2 x 16	bottleneck	6	24	2	2
56^2 x 24	bottleneck	6	32	3	2
28^2 x 32	bottleneck	6	64	2	2
28^2 x 64	bottleneck	6	96	3	1
14^2 x 96	bottleneck	6	160	3	2
7^2 x 160	bottleneck	6	320	1	1
7^2 x 320	Conv2d 1x1	-	1280	1	1
7^2 x 1280	Avgpool 7x7		-	1	-
1 x 1 x k	Conv2d 1x1	-	k	-	

- MobileNet-V2

  MobileNet-V2 [33], as a significant advancement in mobile model performance. It builds on the success of MobileNet 1 by introducing a new inversed residual structure. The focus of this architecture is efficient processing for mobile devices. Unlike traditional residual blocks, MobileNet-V2 uses inverted residual blocks where the input and output have thin bottleneck layers. This design allows for more efficient processing while maintaining accuracy. Similar to MobileNet-V1, MobileNet-V2 uses depth-separable convolutions. These convolutions are divided into depth and point convolution. The depth convolution step applies 3x3 kernels to each channel of the input image. The pointwise convolution follows this. In this step, the outputs of the depth-wise layer are combined by means of 1x1 convolutions to create new features. MobileNet-V2 starts with one fully convolutional layer, followed by 19 inverse residual convolutions (see Table. 3). For efficient feature extraction, each bottleneck uses depth-separable convolutions. The extracted features can then be used for image recognition.

Table 3. MobileNet-V2 Layers

Type/Stride	Filter Shape	Input Size
Conv /s2	3 x 3 x 3 x 32	224 x 224 x 3
Conv dw /s1	3 x 3 x 32 dw	112 x 112 x 32
Conv / s1	1 x 1 x 32 x 64	112 x 112 x 32
Conv dw / s2	3 x 3 x 64 dw	112 x 112 x 64
Conv / s1	1 x1 x 64 x 128	56 x 56 x 64
Conv dw /s1	3 x 3 x 128 dw	56 x 56 x 128
Conv / s1	1 x 1 x 128 x128	56 x 56 x 128
Conv dw / s2	3 x 3 x 128 dw	56 x 56 x 128
Conv / s1	1 x 1 128 x 256	28 x 28 x 128
Conv dw / s1	3 x 3 x 256 dw	28 x 28 x 256
Conv / s1	1 x 1 x 256 x 256	28 x 28 x 256
Conv dw / s2	3 x 3 x 256 dw	28 x 28 x 256
Conv / s1	1 x 1 x 256 x 512	14 x 14 256
5 x Conv dw / s1	3 x 3 x 512 dw	14 x 14 x 512
Conv / s1	1 x 1 x 512 x 512	14 x 14 x 512
Conv dw /s2	3 x 3 x 512 dw	14 x 14 x 512
Conv / s1	1 x 1 x 512 x 1024	7 x 7 x 512
Conv dw / s2	3 x 3 x 1024 dw	7 x 7 x 1024
Conv / s1	1 x 1 x 1024 x 1024	7 x 7 x 1024
Avg Pool / s1	Pool 7 x7	7 x 7 x 1024
FC / s1	1024 x 1000	7 x 7 x 1024
Softmax / s1	Classifier	1 x 1 x 1000

3.2.3. Evaluation metrics

The different deep learning models that are used in our CLD method are evaluated based on several metrics. Adopted metrics involve the commonly used literature: accuracy, loss, recall, and F1_Score. Thus, traditional evaluation metrics such as accuracy (eq1), Loss (eq 2), Precision (eq3), Recall (eq4), and F1-Score (eq5) are used for each disease type to illustrate the performance of the proposed models. Precision measures the accuracy of the positive predictions made by the model, indicating the true positive results among all positive predictions. Recall measures the model's ability to identify correctly all relevant elements, indicating the proportion of true positive results among all actual positives. The F1-Score is the mean of Precision and Recall, presenting the balances between precision and recall in a single metric. It is especially useful for dealing with imbalanced datasets.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \tag{1}$$

$$L(y,p) = \sum yilog(pi) \tag{2}$$

where y represents the true labels and P denotes the predicted probabilities, is used to minimize errors during model training. The negative sign in the formula ensures that the loss decreases as the model improves. The summation, Σ_i, aggregates the loss over all classes, while Yi specifically indicates the true label (0 or 1) for the i-th class.

$$Precision = \frac{TP}{(TP+FP)} \quad (3)$$

$$Recall = \frac{TP}{(TP+FN)} \quad (4)$$

$$F1-score = \frac{2 \times Precission \times Recall}{(Precission+Recall)} \quad (5)$$

With, FP = False Positive, FN = False Negative , TP = True Positive. Emperical results of both dense models (EfficientNet, ResNet50) and Lightweight models (MobileNet-V1, MobileNet-V2) in the basis of these evaluation parameters are depicted in Table 3 and Table 4.

3.3. Exprementation

3.3.1. Dataset

This study proposes a CLD classification method focusing on diseases (Rust, Phoma, Cercospora, Miner) due to their prevalence and severity. All of those CLDs are present in the images of the JMuBEN and JMuBEN2 [34]. For this fact, we have chosen to evaluate our CLD classification method on JMuBEN and JMuBEN2 datasets. The JMuBEN dataset [34] is a valuable resource for researching coffee leaf disease detection and classification. It provides a large and diverse collection of images that can be used to train robust and accurate machine-learning models. The JMuBEN dataset was created by researchers at the University of S˜ao Paulo, Brazil, and is publicly available for download. JMuBEN is a collection of coffee leaf images affected by three different diseases: coffee rust (Hemileia vastatrix), Cercospora leaf spot (Cercospora coffeicola), and Phoma stem canker (Phoma tracheiphila). As well as, JMuBEN2 is a collection of coffee leaf images which are affected by the Miner disease and Healthy coffee leaf images. The images in the JMuBEN and JMuBEN2 datasets were collected from coffee farms in Brazil. The dataset includes 58,555 leaf images classified into five classes: Phoma, Cercospora, Rust, Healthy and Mining (Fig. 5 and Fig. 6). Each image has an annotation with information about the condition of the leaf and whether or not the disease is present.

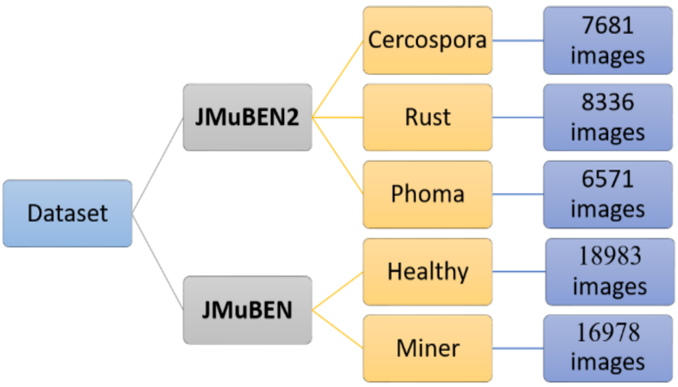

Fig. 5. Coffee leaf diseases available in the dataset

The JMuBEN Arabica coffee leaf image dataset is a valuable resource for training and validating deep learning algorithms for detecting and classifying coffee plant diseases. Researchers have successfully used this dataset to develop machine learning models that have achieved a high accuracy in detecting and classifying multiple coffee leaf diseases. In this context, The JMuBEN dataset has been used in various studies [35]–[37]. The dataset is further split into 3 subsets for training, validation, and testing purposes. Of these images, 20% were used for testing and validation, and the other 80% were used for training. To improve the learning task, further data augmentation and segmentation are applied.

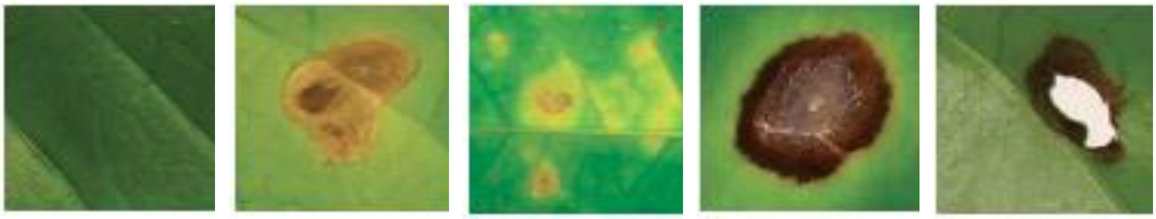

Fig. 6. Samples of different coffee leaf disease classes: a) Healthy, b) Miner, c) Rust, d) Cercospora and e) Phoma

3.3.2. Setups and Settings

This section presents the used hyper-parameters and the variables that regulate network structure and/or training process. For instance, loss function minimization is performed using the Adam optimizer with a learning rate = 0.0001 (equation 6).

$$\boldsymbol{\theta}_{t+1} = \boldsymbol{\theta}_t - \boldsymbol{\alpha}.\widehat{\boldsymbol{m}}_t / \sqrt{\hat{v}_t + \boldsymbol{\varepsilon}} \tag{6}$$

Where $\boldsymbol{\theta}_t$ represents the model's parameters (weights and biases) at time step t, and $\boldsymbol{\theta}_t + 1$ is the updated parameter. The learning rate α controls the magnitude of the update. $\widehat{\boldsymbol{m}}$ is the estimated first moment (a smoothed version of the gradients), and $\hat{v}_t$ is the estimated second moment (a smoothed version of the squared gradients). $\boldsymbol{\varepsilon}$, a small constant (typically 1×10^{-8}), ensures numerical stability by preventing division by zero. This formula is commonly used in optimization algorithms like Adam to achieve adaptive learning rates.

Also, in Table 4, we present the values of all of the experimental variable and parameter settings . For the softmax equation (Eq.7), given a vector z of real number, z1, z2,...Zn

$$\sigma(z)i = \frac{e^2}{\sum_{i=1}^{n} e^2} \tag{7}$$

Table 4. Experiment setting variables and parameters

Variables	Variable Definitions	Used Values for models training
Batch size	The number of samples used for each training batch.	16
Learning rate	The initial learning rate setting.	0.0001
Training epoch	Total number of training iterations.	10
Optimizer	Optimizes the parameters' update iteratively using training data.	Adam (Eq.1)
Loss	Determines the cross-entropy loss between ground truth and predictions labels.	Categorical crossentropy (Eq.4)
Evaluation metrics	Metrics are employed to assess the accuracy of a classification.	Accuracy (Eq.3)
Output activation function	Activation function used in the output layer of networks for multi-class classification problems	Softmax (Eq.2)

3.3.3. Training and Validation Results

The training process was performed on an NVIDIA T4 enterprise GPU. Training and validation accuracy and the loss of several models (EfficientNet) were plotted to illustrate the training process. The accuracy and loss graphs are depicted in Fig. 7. Curves show that the training process with transfer learning was very quick, and the model achieved good accuracy in just a few epochs.

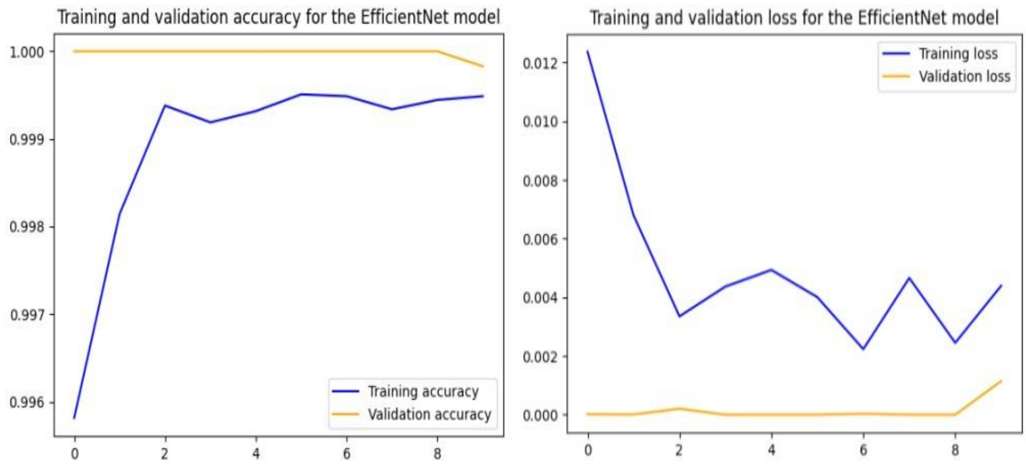

Fig. 7. EfficientNetB0 coupled with Transfer learning's training and validation accuracy and loss

3.3.4. Evaluation Results

The performance evaluation of the models used to classify coffee leaf diseases is shown in this section. To evaluate their efficacy, we used both lightweight and dense models. The models' performance was assessed using three assessment metrics: F1-Score, Precision, and Recall.

Table 5 shows the results for the dense models, providing detailed metrics for each disease class. The dense models were evaluated to determine their robustness and capability in accurately classifying the different types of coffee leaf disease. These models are designed to be more efficient in reducing computational resources while maintaining a high accuracy in disease classification.

Table 5. Results for dense models

	EfficientNetB0			ResNet50		
	Precision	*Recall*	*F1-Score*	*Precision*	*Recall*	*F1-Score*
Cercospora	1.00	1.00	1.00	1.00	1.00	1.00
Healthy	1.00	1.00	1.00	1.00	1.00	1.00
Rust	0.99	0.99	1.00	1.00	0.98	1.00
Miner	1.00	1.00	1.00	1.00	1.00	1.00
Phoma	1.00	1.00	1.00	0.99	1.00	1.00
Accuracy		99.99			99.91	
Loss		1.6274e-5			0.2264	

Table 6 presents the performance metrics for the lightweight models. The results demonstrate how these models perform across different disease categories using the same evaluation metrics.

Table 6. Results for lightweight models

	MobileNet-V1			MobileNet-V2		
	Precision	*Recall*	*F1-Score*	*Precision*	*Recall*	*F1-Score*
Cercospora	1.00	1.00	1.00	1.00	1.00	1.00
Healthy	1.00	1.00	1.00	1.00	1.00	1.00
Rust	1.00	0.98	0.99	0.99	1.00	1.00
Miner	1.00	1.00	1.00	1.00	1.00	1.00
Phoma	0.97	1.00	0.99	0.98	1.00	0.97
Accuracy		99.52			99.62	
Loss		0.8512			0.0242	

According to Table 5 and Table 6, the used models coupled with transfer learning, whose framework was discussed in Section 3, were able to achieve a testing accuracy of 99.99%, 99.91%, and 99.52% for EfficientNetB0, ResNet50, and MobileNet, respectively, and loss was reduced to 0 for EfficientNetB0 after being trained for just 10 epochs. Also, very satisfactory classification performance results were obtained with the MobileNetV1 and V2 models. These results prove that the model is computationally efficient for real-time detection. Hence, MobileNet, coupled with transfer learning, provides accurate research and rapid application of deep learning for CLD detection and classification, which is much needed to address disease propagation. From Table 5 and Table 6, we can see that EfficientNetB0 outperformed the other two models in terms of accuracy on the test set. Furthermore, in this study, EfficientNetB0 was reported to be a successful model for use in coffee leaf disease classification.

4. Results and Discussion

In the following table we present a comparative performance of different models for the classification of coffee leaf disease on the JMuBEN and JMuBEN2 datasets, using metrics such as accuracy, loss, and number of training epochs for each CLD method. Table 7, the EfficientNetB0 model combined with transfer learning shows an exceptional accuracy of about 99.99% and a low loss of 1.627e-5 after only 10 epochs of training.

Table 7. Comparison of our work with the literature

Model	Accuracy(%)	Loss	Training epochs
EfficientNetB0 with transfer Learning	99.99	1.6274e-5	10
ResNet50 with transfer Learning	99.91	0.2264	10
MobileNet with transfer Learning	99.52	0.8512	10
MobileNetV2 with transfer Learning	99.62	0.0242	10
CLIP [38]	85	Unavailable	
CNN + Data Augmentation [39]	95	0.10	500
CNN with MobileNet V2 architecture [24]	98.51	0.2482	96

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Similarly, the ResNet50 and MobileNet models show very encouraging accuracies after using transfer learning: 99.91% and 99.52%, respectively. In contrast, the CLIP model referred to in [33] lags with an accuracy of 85%.

Other models in the literature, including CNN + Data Augmentation [38] and CNN with MobileNet V2 architecture [39], show accuracies ranging from 95% to 98.51%. Moreover, the good performance of our approach is achieved in just a few iterations, as the models efficiently learn the parameters needed for the new classification task in just 10 epochs, whereas models [38] and [39] perform training in 500 and 96 epochs, respectively.

These findings demonstrate that transfer learning is an effective strategy for early detection of coffee leaf disease, allowing timely implementation of control measures and prevention of disease spread. In fact, deep learning models can analyze leaves' images for an early detection of plant disease's signs. The algorithms we have developed are an accurate means of detection that farmers can use to monitor their crops for signs of disease detection and then implement targeted interventions, such as crop rotation or pesticide application, to prevent the spread and minimize yield losses. By improving crop management practices and disease prevention strategies, deep learning models can help to increase agricultural productivity and ensure a stable food supply.

5. Conclusion

In summary, our research underscores the critical role of recent technological advances, particularly AI, in revolutionizing agriculture. Early detection and management of diseased coffee leaves is essential to ensure optimal crop health and yield. By exploring transfer learning techniques, we have developed a highly accurate and efficient method of detecting and classifying Coffee Leaf Diseases (CLDs) using deep learning models. Our proposed approach uses transfer learning on pre-trained models such as EfficientNetB0, ResNet50, MobileNetV1, and MobileNetV2, specifically tuned for CLD detection. Five types of coffee leaves are studied: healthy leaves, leaves affected by Phoma disease, leaves with Cercospora spots, leaves with Rust disease, and leaves with Miner disease. Our results highlight the superiority of the EfficientNetB0 model in terms of accuracy, suggesting its potential as a robust solution for coffee leaf classification. The implications of our research extend beyond the laboratory and offer practical applications for coffee growers worldwide. By integrating AI-based image recognition systems into agricultural practices, farmers can detect signs of disease and pest infestation in real-time, enabling timely intervention to mitigate crop damage and optimize yield. To facilitate the implementation of our deep learning model in the agricultural arena, further consideration should be given to data collection, model deployment and user interface design for a mobile application. In addition, discussing best practices for integrating the model into existing agricultural operations would guide future applications and promote sustainable agricultural practices. Furthermore, our research demonstrates the transformative potential of AI in agriculture and lays the foundation for future advances in managing crops and preventing disease. By taking advantage of cutting-edge technologies, we can pave the way for a more resilient and sustainable future for agriculture.

Declarations

Author contribution. Dr. Adel Alkhalil: drafted the work and substantively revised it; approved the submitted version; provided supervision; communication with the responsible foundation' (Ministry of Culture). Dr. Hanen Guessmi and Dr. Nabila Mansouri: reviewed the literature and related works;

acquisition, analysis and interpretation of data; creation of new software used in the work; drafted the work and substantively revised it.

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Conflict of interest. The authors declare no conflict of interest.

Additional information. No additional information is available for this paper.

Data and Software Availability Statements

Ethics approval: We wish to confirm that all aspects of this research involving coffee leaf images have been conducted in accordance with the ethical standards outlined. The study protocol, including public database and deep learning deployment software environments (Kaggel session,…). Availability of data and materials: The proposed framework was tested and validated using a public dataset. The dataset is available from this link: https://data.mendeley.com/datasets/t2r6rszp5c/1

Code availability: To request a code, contact the corresponding author by e-mail: (nabila.elmansouri@crns.rnrt.tn).

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