A Deep Learning-Based System for Plant Disease Detection and Classification in Arabica Coffee Leaves

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A Deep Learning-Based System for Plant Disease Detection and Classification in Arabica Coffee Leaves

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Abstract

Coffee leaf disease is a growing concern to coffee agroforestry, predominantly caused by pathogenic fungi and, to a lesser extent, bacteria and viruses reducing the yield and adversely affecting the quality of the coffee. Detecting and controlling these diseases in their early stages represent formidable challenges, since traditional methods rely on visual observation by experts and often fail in accurate diagnosis. Machine learning (ML) techniques are alternative solutions for automating the classification of plant diseases and with the rapid advancements in deep learning methods, there is a potential to identify and recognize coffee leaf diseases at early stages, thereby supporting efforts to enhance crop yield. However, there is a notable gap in research, particularly regarding the detection of coffee leaf diseases on a larger dataset. This study employs deep learning models and transfer learning approaches, including EfficientNetB0, MobileNetV2, CNN and VGG16, to address multi-class labeling complexities in Arabica coffee leaf disease detection. Utilizing the "JMuBEN" dataset with 58,405 images across five classes, Phoma, Cercospora, Leaf Rust, Miner and one set of healthy leaf images, the research aims to comprehensively assess each model's efficacy. The test accuracy of the models ranged from 32.49% to 99.7% and the best performing model, EfficientNetB0 outperformed all the models in this study giving a test accuracy of 99.72% and an overall F1 score, Recall and Precision of 99.7%. Beyond Arabica, the findings may extend to Robusta and have broader applications in crop disease detection.

Keywords: Arabica Coffee, EfficientNetB0, MobileNetV2, CNN, VGG16.

1. Introduction

1.1.Background

With 2.25 billion cups of coffee consumed daily, coffee is the second most traded commodity and the oldest in the world [1], falling a little short to crude oil, serving jobs to 125 millions of people and generating about $28 billion in taxes in the global market. The Arabica coffee (coffea Arabica L.) holds the distinction of being the most extensively

[1] https://www.forbes.com/sites/kellyphillipserb/2016/09/29/12-quirky-facts-about-coffee-tax-on-national-coffee-day/

cultivated coffee species and on a global scale, there has been a decline in its production whilst the consumption is steadily increasing over time, resulting in substantial economic loss. The International Coffee Association (ICO) has said that there will be a deficit of 7.3 million of coffee bags in the global coffee market and an increase of approximately 25% - 75% above current production level can meet the 2050 production demand[2]. Coffee has a biennial production rhythm where the production is high in one year followed by low production in the next year, thereby leading to a strong economic fluctuation due to the production rhythm and diseases. The yield losses due to pest and diseases in coffee is estimated to be over 38% every year (Cerda, et al., 2017)and the Arabica coffee production is threatened by a variety of coffee pests and diseases (CPaD) (Liebig, 2017), among them, the Coffee Leaf Rust (CLR), Phoma, Miner and Cercospora are notable where certain coffee diseases like the CLR is universal, regardless of the environment conditions. Leaf Rust is seen over 50 countries and is reported to cause 75% of the yield loss where outbreaks are severe (Gichuru, et al., 2021). The first case of CLR was reported in 1912 in Kenya, while the records say that they were seen in 1861 near Lake Victoria (Western Kenya) on wild coffee. The leaf diseases causes stress on the coffee plants by causing defoliation and a reduction in photosynthesis impacting the next year crop as well as significantly reducing the current year's production (Esgario, et al., 2020). The coffee leaf diseases have decimated numerous plantations in the region since 2012, and as devastating it is, had wiped out the entire coffee plantation in Ceylon (now Srilanka) by 1870[3]. Early detection of plant diseases is valuable as measures can be taken to limit the spread of the diseases and protect the crop.

Various machine learning and deep learning techniques have been implemented in crop disease detection using leaf images of the corresponding plants, mostly for food crops. Transfer learning techniques, where pre-trained models are reused on new datasets and have gained popularity in plant disease detection. Nevertheless, the application of these techniques for classifying Arabica coffee disease detection, particularly when considering larger datasets of leaf images is lacking. Using larger datasets, there could be a significant improvement in accuracy and robustness of disease detection models. Additionally, the knowledge acquired from this study could be extended to the detection of diseases in Robusta coffee plants, another major species of coffee. DL has shown promising results in the field of CPaD with a high level of accuracy, supporting agricultural professionals in the recent years. This study focuses on the early identification of diseases in Arabica coffee plants through a comprehensive analysis of leaf images, utilizing the "JMuBEN" [2] dataset developed by Jepkoech et al., in 2021. The JMuBEN dataset is noteworthy for encompassing 58,405 images representing five classes, Phoma (6571 images), Cercospora (7681 images), Rust (8192 images), Healthy (18983 images), Miner (16978 images), captured under authentic field conditions at the Mutira Coffee plantation in Kirinyaga county, Kenya.

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[2] https://www.reuters.com/article/coffee-deficit/global-coffee-market-to-clock-7-3-mln-bag-deficit-in-2022-23-ico-says-idINL8N37Y3XQ/

[3] https://www.bspp.org.uk/wp-content/uploads/2022/11/PP5-Coffee-leaf-rust-rdcd.pdf

This research implements deep learning and transfer learning techniques such as CNN EfficientNetB0, MobileNetV2, and VGG16 to aid in the early disease detection and classification of Arabica coffee plants using digital image analysis. Motivated by the notable achievements of deep learning in agricultural domains, including its success in prediction of crop yield (Muruganantham, et al., 2022), weed identification and pest management (Zhang, et al., 2023), precision farming (Raj, et al., 2022) and soil health monitoring (Wilhelm, et al., 2022), this study aims to enhance efficiency, sustainability, and productivity, showcasing its potential to address challenges in food production and contribute to sustainable agricultural practices.

1.2.Research Question and Objectives

The National Academy of Science in its research on agriculture published a research agenda underscoring the urgency for innovative technology for early and rapid detection of plant diseases and means of preventing them[4]. Following this analysis, a formulated research question addresses this need as: ***"How accurate are deep learning models like CNN, EfficientNetB0, MobileNetV2, and VGG16, in early detection and identification of Arabica coffee plant diseases through leaf image analysis on larger datasets?".***

Arabica coffee disease detection through leaf analysis can not only help farmers to detect the disease at an early stage but also improve the berry quality and increase the crop production with less maintenance cost. This research has identified a reliable way to identify Arabica disease based on their type. To address the above question, the following research objective has been implemented and achieved.

Objective 1: Examine and provide a critical evaluation of recent works published concerning research on the identification of leaf diseases.

Objective 2: Design and develop a technical framework that facilitates the implementation of research on Arabica leaf disease classification

Objective 3: Implement, evaluate, and analyse CNN, MobileNetV2, EfficientNetB0 and VGG16 to gain a better understanding of their functionality

Objective 4: Identify the most effective transfer learning technique in disease detection of Arabica coffee plants and compare the developed models with existing models of related study.

DL based systems have demonstrated superior performance over traditional feature extraction and classification methods, giving faster and more accurate results that is important in agriculture industry. The models employed includes transfer learning techniques EfficientNetB0, MobileNetV2, and VGG16 addressing the challenges in this vital agricultural domain. Evaluation metrics like computational complexity, training time, confusion Matrix, F1 score, precision, and recall are employed to access the

[4] https://nap.nationalacademies.org/read/25059/chapter/1#xii

efficiency of the model with hypertuning of parameters to achieve an optimized result. These metrics collectively provide a comprehensive understanding of the model's performance in disease detection.

2. Related Work

Crop disease detection is an ongoing study in the field of agriculture and a number of research have been focused on disease detection using machine learning and deep learning techniques for leaf images of plants. This section discusses the related work and methodologies implemented using machine learning (ML) and deep learning(DL) techniques and provide an overview of the same.

2.1. Feature selection using ML techniques for disease detection

Machine learning techniques have emerged as a powerful tool in the domain of leaf disease detection. Extensive research has been performed and novel algorithms have been explored for distinguishing between healthy and diseased leaves based on image data by learning the intricate patterns and features associated with different diseases, often outperforming traditional image processing methods.

Coffee Leaf Rust being a devastating leaf disease in the plantations calls for early detection and management by the farmers. This paper(Marin, et al., 2021) emphasize on decision tree models in the detection of severity of CLR implemented on 400 leaf images of coffee plants captured using UAV images in a plantation in Brazil. The images were grouped based on the severity of the CLR and a total of 63 vegetation indices were extracted from the images and the learners were evaluated in a cross-validation method with 10 folders. The authors used rank approach which allowed a 63% reduction in the number of vegetation indices without a substantial decrease in accuracy, enhancing the efficiency of the model. Models based on regression and decision trees like Logistics Model Tree (LMT), J48 (C4.5), ExtraTree, REPTree, Functional Trees, Random Tree and Random forest (RF) were evaluated for classification. LMT emerged as the most effective in predicting CLR disease achieving high F1 values of 0.915 for early CLR (2-5% rust) and 0.875 for later stages (20-40% rust).

A comprehensive methodology was carried out for grape leaf disease classification on 3885 leaf images (Javidana, et al., 2023) where multi-class support vector machine (SVM) was used to diagnose and classify grape leaf diseases into black measles, black rot, and leaf blight. This SVM classifier outperformed DL methods like CNN and GoogleNet with high accuracy of 98.7% after PCA in short time. Background removal and image segmentation performed using K-means clustering, automatic clustering for selecting the Region of Interest (ROI) and to eliminate the need of manual intervention during image segmentation and Relief feature selection method employed to identify the most significant features for disease classification proved to be efficient in the classification process. A similar study by (Harakannanavar, et al., 2022) applied ML techniques like KNN, SVM, and CNN for classification and early disease detection in tomato leaves. The images were resized to 256x256, and Histogram Equalization and K-means clustering were employed for quality improvement and segmentation. The features in the images were extracted using contour tracing followed by Discrete Wavelet Transform, PCA, and GLCM, to extract important features, contributing to the robustness of the model. CNN achieved an impressive accuracy of 99.6% while KNN with 97% and SVM with 88%.

This study (Kabolizadeh, et al., 2023) tells us how selecting the optimal input features in ML models effects the computational efficiency and the classification accuracy. The research classified area under the crops by pre-processing and separating the features of the images into 4 datasets. Dataset 1 to 3 had 78, 53, 65 features respectively and dataset 4 was the result of combining datasets 1, 2, and 3 with 194 features using Sequential Forward Selection (SFS) coupled with SCM and RF which played a significant role in feature selection and image classification. RF showed an overall accuracy (OA) of 91.23% for dataset 4 and kappa coefficient of 0.9, surpassing the accuracy achieved with dataset 2 by approximately 2.5% in OA and 0.03 in the Kappa coefficient. However, it is worth noting from the SFS results that higher accuracy could be achieved when less than 20 features were recruited in classification. Ensemble techniques have demonstrated superior performance in classifying the disease in crops through leaf image analysis. This study (Jain & Jaidka, 2023) used an ensemble of deep learning classification method to classify diseases in mango leaves consisting of 1206 leaf images. SVM was used for feature extraction and ensemble of GLCM plus SGD (Stochastic Gradient Descent), SVGD (GLCM+SGD) was used to classify the diseased and healthy mango leaf images. The hybrid SVGD showed a improved results in terms of all the parameters including accuracy, recall, F1-score, and precision for 5 folds, 10 folds and 20 folds with maximum accuracy of 97.8% being obtained for 20 and 10 folds.

2.2.Deep Learning Techniques for disease detection in leaf images

Deep learning (DP) techniques like the Convolutional Neural Network (CNN) has shown promising results in the detection of plant diseases as they learn incrementally which eliminates the need for hard core feature extraction process. Also, DP can handle complex datasets with high resolution images which the traditional image processing techniques may fail to process.

The following research (Abuhayi & Mossa, 2023) introduces a novel approach for classifying coffee plant diseases by leveraging CNN with feature concatenation. It also tells about the importance of applying appropriate image pre-processing and data augmentation techniques to improve the accuracy. The use of Gaussian filtering for image filtering is a suitable choice, providing optimal results. The images were resized to a standard size in the image pre-processing stage and 3288 images were augmented to 7067 images by which the issue of imbalanced dataset and over fitting can be handled in the dataset. High level features were extracted by GoogleNet and ResNet which were then sent as an input to various classifiers including GLCM, RF, Multi Level Perceptron (MLP), KNN, and DT classifiers. An ensemble approach was used to evaluate the results with the concatenated model dataset showing accuracy of 99.08%, however, the model was time taking when compared to the existing models. This paper (Crespo-Michel, et al., 2023) studied the classification performance for grapes on different datasets which included RGB, greyscale, 8 bit, 12 bit and full datasets by implementing VGG-16, ResNet-50, MobileNet and Inception-V3 with pre-trained weights from imageNet with VGG16 achieving accuracy up to 97.4%. The research emphasizes on how the classification accuracy (CA) varies on the image quality, the resolution and the bit depth of the images captured for fungal spore in grape vine. RGB dataset gave a better CA, however, the grey dataset subset gave very close results for test accuracy, proving that when adequate information is provided, greyscale can perform well.

In this study, the authors implemented an android based predictive model using a modified AlexNet architecture to classify tomato leaf diseases consisting of 18,345 training images and 4,585 testing images, categorizing into ten labels. The data was separated into training and testing data by a 10-fold cross validation approach and the optimizer used was Adam with learning rate of 0.0005. The Evaluation metrics included accuracy, precision, recall, F1 score, and confusion matrix where the best model using the Adam optimizer with specific hyper parameters, achieves a high average accuracy of 98%. Plant village dataset is a widely used dataset for disease detection and pest control in agriculture, mainly by leaf image analysis. This research (Odamea, et al., 2023) using Plant village dataset focused on multi-class classification for leaf disease of potato and tomato plants, categorizing the disease into early blight, healthy, and late blight. Advanced data augmentation technique was applied on 6,652 leaf images and was resized back for classification. The images were normalized from a range 0 to 1 as neural networks performed better with normalized data. ResNet-9 was implemented for the disease detection and was compared with the baseline model, VGG-16 with ResNet-9 outperforming VGG-16 with 99.7% accuracy. The model was interpreted using Saliency map that provides insights into the model to show the region in the images which are most influential in the decision making of the model, an important factor for AI driven systems.

This research makes significant contributions to the intelligent identification of 2816 images of greenhouse cucumber leaf diseases, in scenarios involving similar diseases occurring on the same leaf using EfficientNet-B0-B7 models with the RMSprop, Adam, Radam, Ranger optimizers. EfficientNetB4 demonstrated the highest accuracy among the models, achieving 97.57% on the test set. The study acknowledged computational limitations in using larger models (B5-B7) due to GPU constraints. The study highlighted the importance of the Ranger optimizer, showcasing its effectiveness in improving accuracy for the challenging task of classifying similar diseases. To detect the Bacteriosis in peach leaves, a novel LightWeight (WLNet) CNN model based on VGG-19 was built (Akbar, et al., 2022) using the ReLu activation function on 10,000 synthetically created leaf images which was then compared with models like AlexNet, VGG-16, LeNet, and VGG-19. It was seen that the top convolution layers couldn't identify the features well and hence they are removed to detect broad features having fewer filters. The proposed WLNet model was evaluated with different metrics like Accuracy, Precision, Recall, F-Measure, Confusion Matrix, and MSE and was able to achieve 98.74% when trained with

50 epochs. The prominence of this research was that this architecture can be able to classify CT scan images of brain, lung x-rays, liver, kidney and other biological diseases.

In this research (Sorte, et al., 2019), to detect Cercospora and Rust in Robusta coffee leaves, two approaches were explored for disease recognition, Texture Attribute experiment and DL. The texture attributes involved statistical attributes and local binary patterns for feature extraction with feed forward neural network being trained with these attributes. The DL model used a modified version of AlexNet on few samples and compressed images of 128*128. The DL approach outperformed the Texture Based Disease Recognition approach 0.97 Kappa co-efficiency. This study (Esgario, et al., 2022) classifies 5 types of coffee leaf diseases using CNN and transfer learning. The dataset contained 1747 images of coffee leaves. The dataset was pre-processed by cropping the images to remove unwanted details and focus on the symptomatic features followed by data augmentation, increasing the image count to 2147. Inception V3 model consisting of 48 layers was implemented where the model was trained with images from ImageNet and to optimize the model, Mini-Batch Gradient Descent algorithm was implemented giving an accuracy of 97.07%. The study (Kuswidiyanto, et al., 2023) addresses downy mildew disease in kimchi cabbage, a significant agricultural product in Korea. The images were captured from airborne hyper spectral systems and ReGB band composition was used to visualize early disease symptoms. This implementation uses SLIC algorithm to generate a leaf-by-leaf dataset and DBSCAN algorithm to group nearby leaves for disease severity assessment which was then trained using 3D-ResNet model, with four residual blocks with ReLu activation function and a max-pooling layer achieving an accuracy of 0.873.

While extensive research has explored the application of machine learning techniques in agriculture, particularly in classifying and identifying plant diseases through leaf images, there remains a notable gap in utilizing these techniques for the classification of Arabica coffee diseases, especially on large datasets like the "JMuBEN Coffee Dataset" consisting of 58,405 images, published in 2021. This study seizes the opportunity to delve into the dataset, aiming to develop a robust and reliable approach for accurately detecting various diseases in Arabica coffee plants. Specifically, the study focuses on employing transfer learning models such as EfficientNetB0, MobileNetV2, CNN and VGG16 to address multi-class labelling complexities in Arabica coffee leaf disease detection. Overall, the objective is to contribute to the creation of precise, reliable, and interpretable disease detection models that can offer valuable insights to coffee growers and the broader agricultural community.

3. Research Methodology

This section briefs about the research methodology in detail. Also, step by step details on the implementation part with the technical aspects will be explained here. Since our main objective is to identify the disease and classify them based on the leaf images, KDD is used, as it is the cornerstone of our investigation, guiding the systematic process of extracting meaningful patterns and insights from the dataset.

3.1. KDD (Knowledge Discovery in Databases)

Our main objective of the project is to classify the coffee leaf diseases into diseased classes and healthy class, and hence, KDD is used. It is an iterative approach where knowledge acquired gets transmitted back into the process thereby enhancing the efficacy of established objectives. It is a general procedure for discovering knowledge in data from larger datasets by extraction of patterns and information using machine learning (Saltz & Hotz, 2020). It helps us helps identify anomalies efficiently because the entire process segregates working into different steps. Figure 1 shows the process flow diagram consisting of different phases right from Data gathering, Exploratory Data Analysis (EDA), Pre-processing the data, Feature extraction, model building, classification of Arabica leaf disease and evaluation.

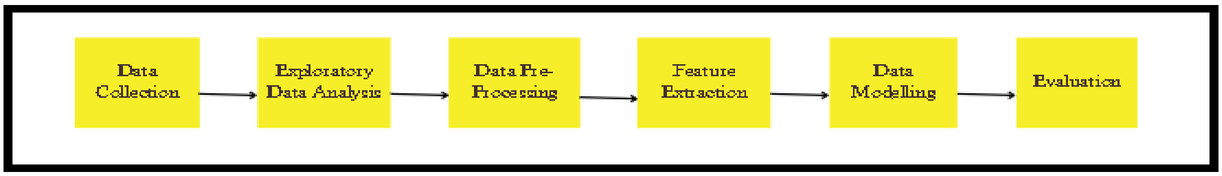

Fig 1. KDD methodology used in coffee leaf disease detection

3.2. Data Collection

Data Gathering is a crucial step before giving a solution to any problem when it comes to machine learning as the right data will help in building accurate and more reliable model. The main problem facing the coffee leaves is the biotic stress and CLR being a major outbreak in coffee plantations leading to reduced yields and compromised bean quality. Efforts to mitigate the impact such diseases on coffee plants have become a critical area of research and intervention which has provided valuable insights to the research in understanding the specific needs and formulating the research question tailored to address those needs. One key aspect of addressing this challenge is the development of accurate and reliable models for early detection and classification of unhealthy coffee leaves. The dataset for this project is the "JMuBEN" dataset that was mainly created with the objective of addressing the scarcity of Arabica coffee leaf images online[5]. This dataset comprises of four categories of unhealthy images i.e. Phoma, Cerscospora, Rust and Miner) and one class of healthy leaf images with a total of 58,405 leaf images for research purpose. The images were captured under real-world conditions from Mutira Coffee plantation in Kirinyaga County, Kenya which is one of the leading producers of high-quality Arabica coffee.

3.3. Exploratory Data Analysis (EDA)

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[5] https://www.kaggle.com/datasets/noamaanabdulazeem/jmuben-coffee-dataset

EDA is an important step in data analysis which involves data exploration and summarizing the key characteristics of the dataset to gain insights into the dataset. For the JMuBEN dataset, EDA was performed using pandas library to understand the distribution of coffee leaf categories and was found that Phoma class has 11.25% of the total images, Cercospora contained 13.15%, Leaf Rust with 14.03%, Miner consisting of 29.07% and healthy leaf images taking 32.50% of the overall percentage as shown in Fig 4.

3.4. Data Pre-processing

The images from the downloaded sample contained 58,405 images from all 5 classes. The leaf image dataset contains images that are cropped and suited to enable training and validation using deep learning techniques and hence, there is no unwanted noise in the images like the background noise. Neural networks require large dataset for training which basically calls for data augmentation. Here, the dataset has large number of images for training and hence, we can skip the process of data augmentation.

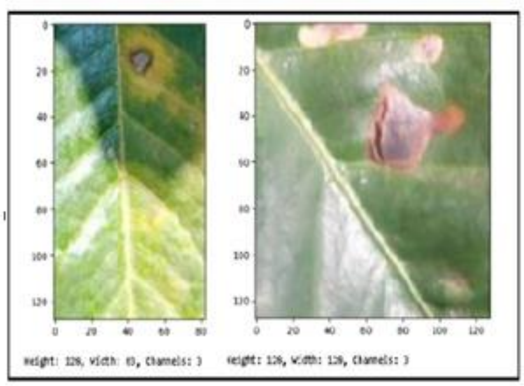

Fig 2. Images of different dimension

Fig 3. Coffee Images after resizing

The dataset is a pre-processed image where the images are cropped to highlight the region of interest of the disease where it is visually apparent. Also the images are resized to ensure uniformity in shape and size, which is essential for effective deep learning model training. Mostly the images are standardized to a resolution of 128x128 pixels, however, there were images of different resolution of 83x128, 101x256, 126x256, 117x256 and so on. Figure 2 shows the images of different resolution. Since the image size is different, the images are rescaled to a size of 128x128 using the PIL library; this ensures consistency in data format and reduces computational complexity. Figure 3 shows the leaf images after resizing.

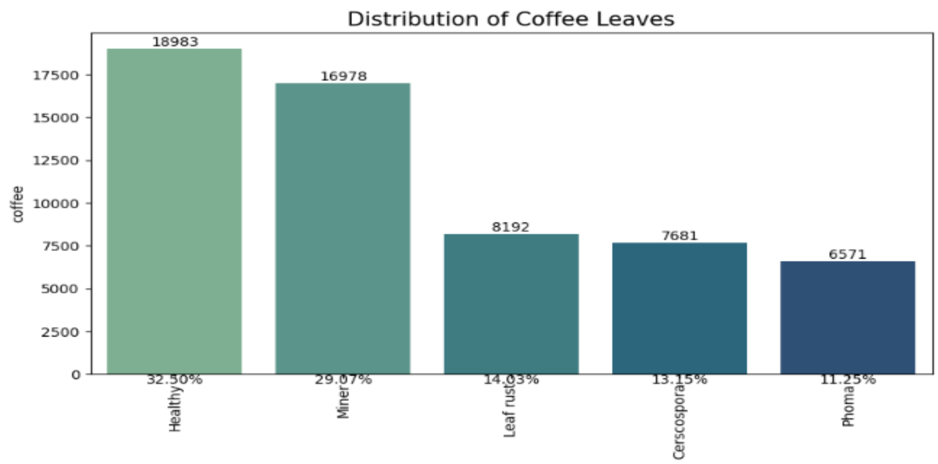

Fig 4. Distribution of 5 classes of coffee leaves

3.5. Feature Extraction

Feature extraction is an important role in image processing where the features in digital images like edges, shapes and motions are detected. The process involves image segmentation and selecting key features from the images that will help in subsequent classification. In the realm of deep learning (DL) algorithms, feature extraction is seamlessly achieved in an automatic manner by the filters in the layers of the network, minimizing the need for extensive human effort and domain-specific knowledge (Ngugi, et al., 2020). DL algorithms operate with a multi-layer data representation architecture, where the initial layers focus on extracting low-level features, and subsequent layers progressively capture high-level features. In this research, the CNN architecture takes handles the feature extraction process and trains the models based on these extracted features.

3.6. Model Training

Extensive research has prioritized sustainable, disease-free crops, with a notable shift towards automatic disease detection using machine learning in agriculture. Leaf image analysis to detect crop disease has played a vital role and a vast amount of visual data is produced by the scientist and researchers in agriculture industry. Numerous classification models have been built to automatically detect plant diseases through leaf image analysis. A comprehensive literature review indicates that deep learning models and transfer learning techniques outperform traditional approaches in this domain. In this research, different transfer learning models like CNN, EfficientNetB0, MobileNetV2, and VGG16 have been employed. The exploration aims to provide a comprehensive understanding of the strengths and weaknesses of each model, shedding light on their effectiveness in addressing the complexities of the multi-class label problem in the context of leaf disease detection in Arabica coffee leaves. Fig 5 shows the workflow diagram of the model. The leaf image are resized in the data pre-processing phase and is trained by pre-trained models like CNN, EfficientNetB0, MobileNetV2 and VGG16 where the convolutional layer, max pooling layer and dense layer help in feature extraction by selecting intricate patterns from the leaf images and classifying them into appropriate classes. The model is tested and then analysed for their performance through various evaluation metrics like test accuracy, computational complexity, F1 score, precision, recall and training time and the best performing models are proposed for further use.

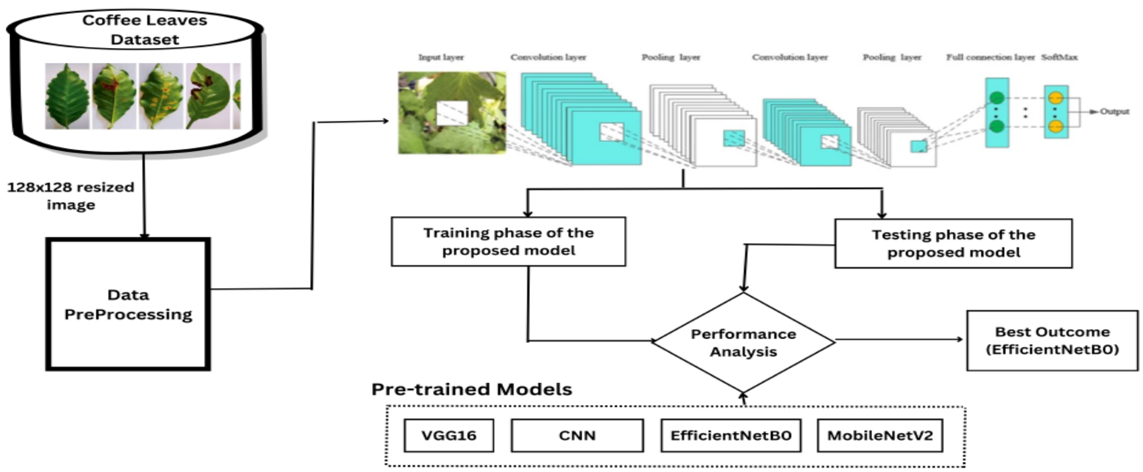

Fig 5. Workflow diagram of the model

3.7. Model Evaluation and Presentation

It is important to evaluate the trained models to assess its performance by testing it on unseen image dataset and to determine its adaptability to new scenarios. This evaluation process serves the dual purpose of comparing different models, gauging their effectiveness in addressing the research problem, and determining the best suitable solution for the research problem. The evaluation of multi-class classification models for coffee disease detection involves assessing their performance using key metrics such as F1 score, Precision, Recall, computational complexity, training time, confusion matrix and test accuracy. In conclusion phase, the implemented models are compared with these metrics in a tabular form accompanied by an explanation for the selection of the best-performing model. Additionally, graphical representations illustrating the training progress, including training and validation accuracy, as well as training and validation loss, are provided based on the available training history.

4. Design Specification

Design specification plays a pivotal role in the development process by providing a comprehensive and clear outline of the requirements for the models. This section outlines about the detailed requirements of the models, the features and high-level functionalities of the architecture and algorithms used. Additionally, the evaluation metrics to gauge the performance of these models is discussed here.

4.1. Modeling Technique

This section delves into the modelling technique used in the study: CNN, VGG16, EfficientNetB0 and MobileNet. The main aim here is to understand the unique characteristics of each of these algorithms with their design details that make these models effective for detecting diseases in Arabica coffee leaves. Also, we will explore how each model is structured and what specific features contribute to their success in identifying and classifying different diseases affecting coffee plants.

CNN is a deep learning architecture, employed mainly for image recognition which can extract relevant features without human interference as the structure of network in CNN is designed to that of neurons of a human brain (Alzubaidi, et al., 2021). The architecture includes convolutional and pooling layers which allow them to automatically learn and recognize hierarchical features in images. CNN models have proved efficient in image classification due to their capacity for feature extraction and weight sharing, making them a cornerstone in image processing. MobileNet is a simple, lightweight and efficient CNN which uses depthwise separable convolutions where it applies only one convolution for every input channel and the channel dimension of output image will be same as that if the input (Sandler et al., 2019). The pointwise convolution is the last stage in filtering where the features created by depthwise convolution is merged to one. The uniqueness lies in its efficiency, parameter reduction through depthwise separable convolutions, lightweight architectural design, channel wise processing, and adaptability for balancing between model size, accuracy, and deployment speed based on diverse application requirements.

VGG16 is a 16 layered deep neural network consisting of 3 fully connected layers and 13 convolution layers(Simonyan & Zisserman, 2014) and works on the principle of multiple stacked convolutional blocks to increase the networks depth, thereby capturing the complex features automatically. The layers in the network are uniform and consistent which allows visualizations of the feature maps to be clear such that the learning process of the features through forward propagation can be observed. This design choice makes VGG16 a prominent and recognizable model in the field of image classification and deep learning. EfficientNetB0 is a CNN, developed by Google AI researchers which uses compound coefficient as a scaling method to uniformly scale all the dimensions such as the network depth, width, and resolution. If the input image size is bigger, then more layers and channels are added to capture the fine-grained patterns of the image with 10x better efficiency compared to the state-of-the-art accuracy in image classification tasks while utilizing significantly fewer parameters compared to other architectures, making it a go to choice for scenarios with limited computational resources.

4.2. Evaluation Technique

To evaluate the performance of the models and to determine the optimal one for our study, accuracy, F1 score, Precision, Recall, training time, computational complexity and confusion metrics are used. These metrics are saved in a .csv file for each model for all three experiments and also, the confusion matrix, providing insights into classification results, is saved as a .jpg file for each respective model.

5. Implementation

The implementation process involves several procedures to develop a machine learning model that not only functions effectively but can also be deployed and utilized successfully in real world scenarios.

5.1. Tools Used

The project code implementation was developed using Python programming language with Jupyter as the IDE within the Anaconda platform. Anaconda is an open-source platform which has extensive libraries for data processing, predictive analysis, and data mining through python programming. Jupyter notebook is an open-source web based application that helps in code execution, data processing and data visualizations. Matplotlib, a python library has been utilized for creating graphs during EDA and matrix evaluation. This project uses keras as a neural network API, built on top of TensorFlow architecture. It provides flexibility for developing various frameworks including CNN and Deep Neural Networks (DNN).

5.2. Data Selection

The coffee leaf images are taken from JMuBEN dataset available in Kaggle and are publically accessible for researchers to develop deep learning models to aid in coffee disease recognition and classification. Since neither the website nor the stakeholders of the data have requested any special authorization to access the data, this research doesn’t violate any ethical and moral standards. A total of 58405 Arabica coffee leaves images belonging to 5 classes Rust, Phoma, Cercospora, Healthy and Miner are used for classification where the dataset is loaded differently for three different experiments consisting of 40881 training set, 11685 validation set and 5839 test sets to gain insights into its robustness and generalization capabilities. This also helps in fair comparison between models and provides a systematic and controlled approach to assessing the model's performance under various conditions.

5.3. Implementation of the Deep Learning Models.

CNN is implemented as one of the deep learning model in this research for coffee leaf disease detection and classification. This architecture uses 3x3 convolutional layers where the input layers take an image size of 128x128 with RGB colour channels. The first and second layers both have 32 filters with kernel size of 5 and 3 respectively to aid in extracting specific features from the images with ReLu as their activation function. This is followed by MaxPooling layer of pool size 3 to retain the important features. The flatten layer flattens the output from the convolutional layers into a 1D array before passing it to the dense layers. The final classification is performed at the output layer with dense layer of 512 units and ReLU activation function with a dropout of 0.25 to prevent over fitting with softmax activation function in the output layer. A batch size of 32 is used for 5 classes and is trained over 30 epochs with a patience of 30. In the model compilation phase, categorical cross entropy is used for multi class classification tasks and RMSprop optimizer (Root Mean Square Propagation) has been used with learning rate of 0.0001. The CNN model was initially trained with sigmoid as the activation function in the dense layer for 20 epochs for one set of training images and there was a higher training time with an accuracy of 73.4%. To improve the accuracy, multiple activation functions like tanh and softmax was implemented where softmax gave better results and the same has been used in the implementation.

MobileNet is used in this project because of its lightweight nature as it is more efficient in terms of memory usage and computational resources. The MobileNetV2 base model is set up without pre-trained weights where the model will be trained from scratch. The input layer takes image of size 128x128 with three colour channels, RGB. The last second layer of MobileNetV2 is extracted and flattened to convert the 3D feature maps into a 1D vector. This is followed by addition of two fully connected layers with 512 units and ReLu activation function. The first convolutional layer has a filter of size 32 and a kernel size of 3 and ReLu as its activation function. Batch normalization and ReLu activation are applied after each convolutional layer to stabilize training and introduce non-linearity. The last output layer has 5 units with softmax activation function as it its ability lies in converting raw output scores into probability distributions over multiple classes.

This project implements a customized VGG16 where second-to-last layer responsible for classification in the original VGG16 is created. The input layer is set to take images with dimensions 128x128 and RGB colour channels for 5 classes, followed by max pooling in the convolutional layers. The last output layer in the VGG16 model is flattened and a dense layer 512 units and ReLu activation is added. The model is compiled with categorical cross entropy loss, RMSprop optimizer with a learning rate of 0.0004. This model was initially implemented on one set of training dataset and tested for the same with 20 epochs using tanh and sigmoid activation function in the dense layer with average pooling. The training time was 7 hours which is notably high with accuracy of 17.3%. To overcome the vanishing gradient problem, ReLu was used with softmax as the activation function in the final layer and the model is trained and tested across three experiments, each comprising 30 epochs.

EfficientNetB0 is baseline model in EfficientNet family designed to address the issue of scaling in models, and also offers a balanced trade-off between computational efficiency and top-tier accuracy where it uniformly adjusts the depth, width, and resolution, thereby, ensuring efficient use of computational resources. This research uses EfficientNetB0 in classification of coffee leaves for disease detection because of its scalability. The architecture includes three convolutional layers, max-pooling layers, and dense layers, complied with RMSprop optimizer and categorical cross entropy with a learning rate of 0.0004. The input image that the input layer takes is 128x128 with RGB colour combination and the batch size is set as 32 for 5 classes and the model is run for 30 epochs with patience as 30. This underlying EfficientNetB0 model is then extended by the function by adding additional layers for specialized categorization. It flattens the output of the previous layer, and then applies a dense layer with 512 units and ReLU activation, and finally a dense layer with softmax activation for the final classification.

6. Evaluation

Evaluation is an important step in solving deep learning models as it helps us assess the performance of implemented models through various metrics. In this project, the model's performance is outlined in terms of accuracy and loss in training, validation and testing sets along with other metrics like total training time, F1 score, Precision, Recall, Computational complexity and confusion matrix. Four distinct models, CNN, MobileNet, EfficientNetB0, and VGG16 are evaluated, and their performance is scrutinized in terms of these metrics. Table 1 shows the results of all the four models and based on the evaluation results, the effectiveness of each model is assessed in this section.

Table 1. Evaluation metrics for the implemented models

Model	Experiment	Total Parameters	Computational complexity	Epochs	Training Time (sec)	Test Accuracy	F1 score	Precision	Recall
CNN	1	2130405	0.006389307	26	1215.39934	0.988749971	0.98607083	0.98612203	0.986063329
CNN	2	2130405	0.008519076	27	2455.786722	0.990049971	0.99002882	0.99003124	0.990029782
CNN	3	2130405	0.010648845	21	3456.49046	0.986249974	0.99743498	0.99746535	0.997432606
MobileNet	1	2916421	0.002916066	30	5135.646533	0.324946513	0.15938792	0.10559024	0.324946513
MobileNet	2	2916421	0.005832132	30	5221.958424	0.324946513	0.15938792	0.10559024	0.324946513
MobileNet	3	2916421	0.008748198	30	5552.077375	0.324946513	0.15938792	0.10559024	0.324946513
VGG16	1	14979909	0.02995	30	13374.04104	0.3249	0.1594	0.1056	0.3249
VGG16	2	14979909	0.044926	30	13126.92368	0.324947	0.159388	0.10559	0.324947
VGG16	3	14979909	0.059901	30	13499.01288	0.379033	0.253109	0.279489	0.379033
EfficientNetB0	1	22854437	0.082772172	30	10665.98857	0.999725019	0.99972502	0.99972502	0.999725019
EfficientNetB0	2	22854437	0.105643596	30	11026.9336	0.996321479	0.99632148	0.99632148	0.996321479
EfficientNetB0	3	22854437	0.12851502	30	11864.5017	0.991787812	0.99178781	0.99178781	0.991787812

6.1. Evaluation of CNN

CNN has been implemented for disease detection and classification in coffee leaves for three subsets of data called experiments. The model is trained with 2,130,405 parameters across all experiments and with 30 epochs, and early stopping incorporated for all 3 experiments of data to evaluate its generalization performance. The testing phase involved assessing model's performance on a separate test dataset, generating confusion matrices to evaluate classification accuracy. Computational efficiency was quantified using GFLOPS metrics. From table 1, we can see that there was consistent high test accuracy across all the experiments ranging between 98% to 99% with efficient training time ranging from approximately 836 to 1073 seconds. The F1 score, precision, and recall are also consistently high, indicating a balanced performance and individual prediction results of each class ranging from 0.986 to 1. Figure 6 shows the accuracy and Confusion Matrix for CNN implementation for experiment 2 dataset after training.

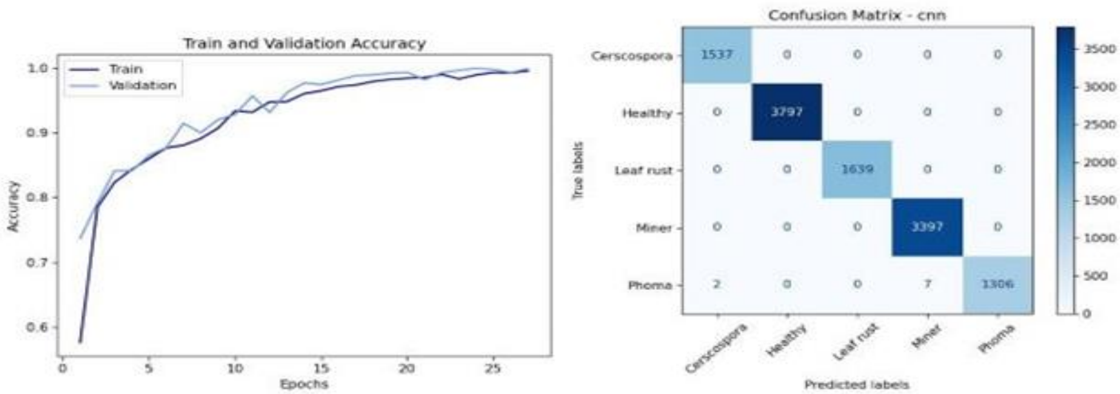

Fig 6. Plot of Accuracy, and Confusion Matrix for CNN implementation

It can be inferred from the figure that the validation accuracy increases with increase in epochs and at an epoch of 25, the accuracy reaches a peak of 99% and remains constant thereafter. Also, the confusion matrix shows that the model mostly predicted true positives. It can also be seen that the model is performing well as there is no significant difference between the train and validation curve which in turn suggests that the model is not overfitting. This model achieved an overall test accuracy of 99.00% in experiment 2 for 27 epochs with computational complexity of 0.006389307.

6.2. Evaluation of MobileNetV2

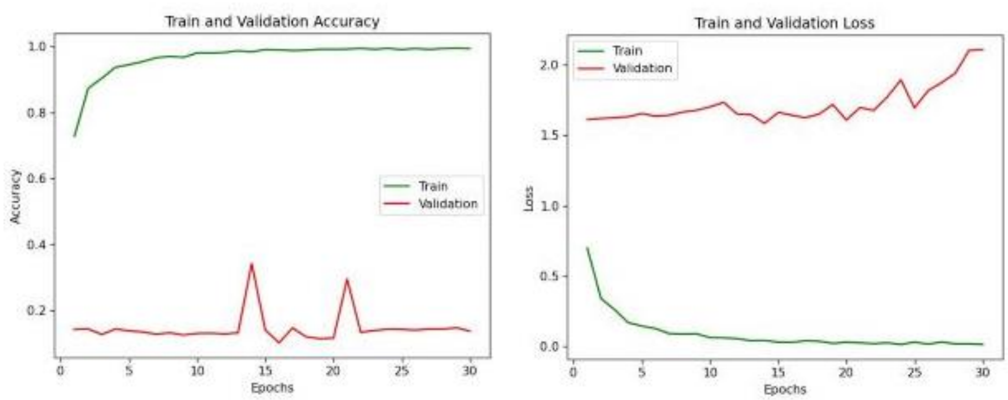

Fig 7.Plot of Accuracy and Loss for MobileNetV2 Implementation

The model was trained with total parameters of 2,916,421 for training with batch size set to 32 and rescaled images of 128*128 with sigmoid activation function. This model showed poor accuracy of about 31.47, however, the execution time was comparatively faster from the rest of the model run. To improve the performance of the model, hypertuning was done where softmax activation function was used. However, these adjustments did not yield significant improvements as the model has a consistent accuracy of 32.4% across all experiments with F1 score, precision, and recall being consistently low at 15.94%, 10.56%, and 32.5%, respectively with individual class results showing either 0 or 1 where all results were misclassified except for healthy leaf images. Figure 7 shows the accuracy and loss curve for MobileNetV2 implementation for experiment 3 of dataset after training. The model shows that the training accuracy is increasing and reaches a constant after 30 epochs, however the validation accuracy does not seem to improve and attains a constant of 10% after 23 epochs with computational complexity of 0.008748198.

6.3. Evaluation of VGG16

This model was trained with 14979909 parameters for 30 epochs over all three experiments. Notably, there was an increase in the accuracy after tuning and the test accuracy remained consistent around 32.5% in the initial two experiments, while a modest improvement to 37.9% is observed in the third experiment in terms of accuracy, F1 score, precision, and recall, however still having a high training time of 3.8 hours. Fig 8 depicts the accuracy and loss for VGG16 implementation for experiment 2 dataset after training giving a computational complexity of 0.059901 where the individual class results were mostly misclassified except for healthy class images. It can be inferred that the train and validation accuracy lies in the range of 30.6% to 34.5% with no major increase as the epoch increases. However, the model is learning relatively well as the loss is gradually decreasing.

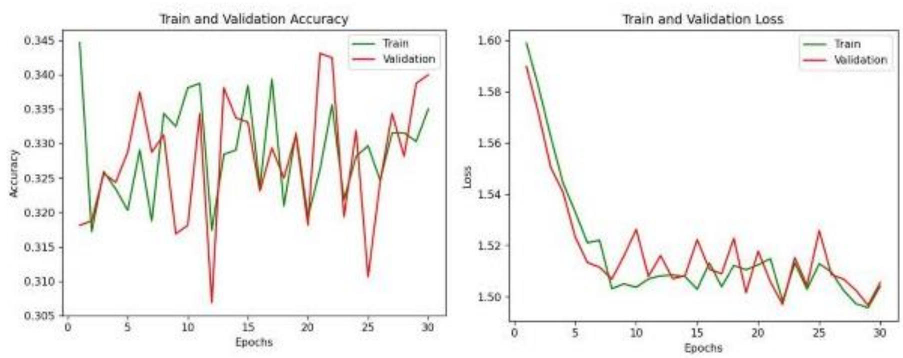

Fig 8. Plot of Accuracy and Loss curve for VGG16 implementation

The poor test accuracy even after hypertuning (Saleem, et al., 2020) suggests that VGG16 architecture is not effective for disease detection for larger dataset and for classification in coffee leaf.

6.4. Evaluation of EfficientNetB0

The model was trained with a total of 22,854,437 trainable parameters across all 3 experiments with a learning rate of 0.0004 for 30 epochs. Categorical cross entropy is used as the loss function for this multiclass classification problem with RMSProp optimizer. Fig 9 shows the accuracy, and Confusion Matrix of EfficientNetB0 model with a near perfect accuracy curve and almost all values predicting true positives resulting in a precision of 1 for all classes except for Phoma, which showed 0.999. All the experiments achieved a F1 score above 99% with experiment 1 showing exceptional accuracy, F1 score, Precision and recall of 99.7%. The model also has a training time of 2.9 hours approximately with computational complexity of 0.082772172 which is reasonable given the complexity of training a deep neural network.

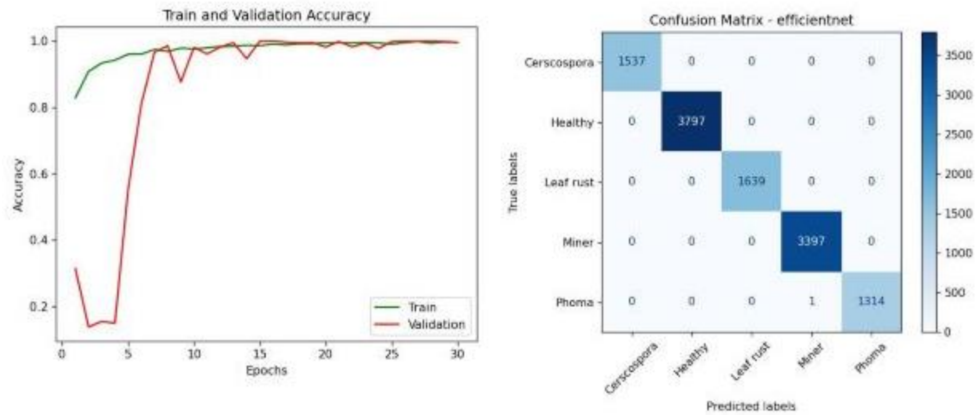

Fig 9. Plot of Accuracy, Loss and Confusion Matrix for EfficientNetB0 Implementation

6.5. Discussion

Coffee leaf disease is a major threat for coffee growers and its yield loss is a economic loss worldwide. Several research and studies have been carried on to battle disease in plants using machine learning and deep learning techniques in the recent years. Deep learning techniques have been showing promising results and, in this research, CNN, MobileNet, VGG16 and EfficientNetB0 techniques are used for Arabica coffee leaves disease detection and classification using the JMuBEN dataset consisting of 58,405 leaf images, classified into five classes. The findings of these techniques are discussed here in terms of accuracy, F1 score, Precision, recall and training time. Table 2, shows the evaluation metrics of best performing experiments for the implemented model.

From the table 2, we can infer that CNN model performed well in terms of accuracy of 99% with F1 score, precision and recall of 99.92% taking about 2456 seconds to train. Despite having a lower test accuracy of 32.50%, MobileNetV2 was trained comparatively faster given the complexity of the dataset. However, the F1 score, precision, recall still remained low indicating that the model was not suitable for disease detection in coffee plants having larger datasets. VGG16, with a test accuracy of 37.90%, demonstrates a balanced performance in terms of F1 score, precision, and recall ranging from 0.25 to 0.37, however, the time taken to train the model was 13499 seconds indicating an unreliable model for classification. Notably, EfficientNetB0 emerges as the best performing model with an exceptional accuracy of 99.97%, and a near perfect F1 score, precision, and recall of 99.97% taking 10666 seconds to train the model, outperforming VGG16 and MobileNetV2.

Table 2. Evaluation metrics of best performing experiments for implemented models.

Model	Test Accuracy	Training Time (sec)	F1 score	Precision	Recall
CNN	0.99004997	2455.786722	0.999228823	0.999231	0.999229782
MobileNetV2	0.32494651	5135.646533	0.159387923	0.10559	0.324946513
VGG16	0.379033	13499.01288	0.253109	0.279489	0.379033
EfficientNetB0	0.99972502	10665.98857	0.999725019	0.999725	0.999725019

Regarding the classification of coffee biotic stress, the most similar work is compared as presented in table 3 and the work by (Yamashita & Leite, 2023) who conducted experiments to identify 6 kinds of leaf diseases in coffee leaves for 4667 samples achieved a accuracy of 98% by cascade method while another study (Esgario, et al., 2020), achieved an accuracy of 95.24% for 2722 images classifying 4 kinds of coffee leaf diseases.

Table 3. Comparison of models of related study

Author Name	Dataset Size	Model Name	Accuracy
Yamashita et al;(2023)	4667	MobileNet	98
Esgarioa et al;(2020)	2722	ResNet50	95.24
Manoj et al;(2020)	2147	CNN	97.61
Javierto et al;(2021)	1747	YOLOv3,MobileNetv2	90
Harshitha P.S. (2023)	58405	EfficientNetB0	99.97

The study by (Kumar, et al., 2020) also involved classifying Phoma, leaf rust, Cercospora, miner and healthy leaf diseases achieved an accuracy of 97.61% for 2147 leaf images and that of (Javierto, et al., 2021)yielded a result of 90% in classification of Robusta coffee leaves for 5 classes of leaf disease. Although the results were higher, this project research gave an exceptional accuracy of 99.97% for a larger dataset using EfficientNet architecture. Also, the images were captured under a real-world conditions which is advantageous for practical application. On a whole, EfficientNetB0 proves to be the most effective model for Arabica coffee leaf disease detection, showcasing superior accuracy and efficiency in comparison to other models.

7. Conclusion, Limitations and Future Work

Deep learning techniques have showed promising results in crop protection as the key to manage widespread of the disease is rapid detection. The pivotal research question guiding this study is: *"How accurate are deep learning models like CNN, EfficientNetB0, MobileNetV2, and VGG16, in early detection and identification of Arabica coffee plant diseases through leaf image analysis on larger datasets?"*. Through this research, four deep learning techniques, EfficientNetB0, MobileNetV2, CNN and VGG16 have been implemented for the detection of coffee leaf diseases and its classification into five distinct classes, Phoma, Cercospora, Leaf Rust, Miner and healthy leaf images. The study highlights the effectiveness of deep learning methodologies in identifying and classifying the diseases affecting coffee plants. The accuracy obtained by the models EfficientNetB0 with 99.97% and CNN with 99% highlights the capacity of deep neural networks to learn intricate patterns and attributes within images of diseased leaves on larger dataset. This reveals the model's ability to identify features through patterns which is not possible for a common man without specialized knowledge.

The images in the dataset were cropped with the region of interest for research purpose, which could be considered as a limitation for the practical application of the proposed system, as in real scenario, the entire leaf image will be used in disease detection. This suggests that training the model with the original full leaf images could provide a more realistic representation of the challenges faced in practical applications. An appropriate approach would be to train the model with dataset having its original full leaf image and analysing the results with the proposed model. Also, the best performing model, efficientNetB0 took approximately 2.9 hours to train the model. This could be improved by having a dedicated GPU for training which can handle parallel processing making the model run faster. While, efficientNetB0 and CNN performed well, MobileNet and VGG16 gave poor accuracy with misclassification of results taking considerably large amount of time to execute. This could be improved using ensemble techniques where techniques like bagging, voting or stacking can be applied to combine multiple models and improve the prediction of the results.

The study on the application of deep learning techniques for Arabica coffee leaf disease detection holds numerous benefits for various stakeholders. Plantation owners and coffee growers benefit from this research by ensuring early and accurate identification of diseases, thereby preventing crop loss at an early stage. Robusta is another variety of coffee that is majorly grown in Asia and this study could also be adapted to suit the specific characteristics and disease patterns observed in Robusta plants. Overall, the study's outcomes have practical implications for coffee cultivation, agricultural research, and the advancement of technologies in crop health monitoring.

This research was able to develop techniques that produce reliable models in classifying the coffee leaf diseases, however, the training time for training the dataset is large. As further research, the work can be expanded in tuning the parameters to decrease the training time of the model. Also, various other deep learning and transfer learning techniques on the JMuBEN dataset can be developed. Coffee leaves are not only subjected to one type of disease but can have the occurrence of 2 or more types of fungal and bacteria infestation. Study can be leveraged to identify multiple occurrences of disease in the same plant with the leaf images; thereby models could be developed capable of handling multi-class and multi-label classification scenarios to identify co-occurring diseases in the same plant. By taking these steps, a more reliable system for coffee plant disease detection using leaf image analysis can be achieved and can further help in sustainable agriculture.

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