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Data Analytics

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MSc Project Submission Sheet

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Corn Leaf Disease Detection Using Deep Learning and Explainable AI

Focusing on ResNet50 and MobileNetV2 with Grad-CAM++ & LIME

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ABSTRACT

Plant health is crucial for maintaining agricultural productivity & food security and automated plant disease diagnostics help us achieving this while benefiting the economy. This research work uses advanced deep learning models to analyse early and accurate detection of Maize leaf diseases which include Blight, Common Rust, and Gray Leaf Spot. In this work, ResNet-50 and MobileNetV2 architectures are employed, along with complex data augmentation and transfer learning to enhance classification capability. Namely **Grad CAM++ (Gradient weighted Class Activation Mapping++)** and **LIME (Interpretable Model Agnostic Explanations)**, Explainable AI (XAI) methods enhance model interpretability providing graphical visualization of predictions to get away from the black-box character of these models. After Hyperparameter Tuning MobileNetV2 being a light model gave a decent accuracy of 90.16%, to optimize computational power, for restricted environments. While Resnet-50 model provided a wonderful performance with accuracy of 96%. The complementary application of Grad-CAM++ and LIME demonstrates the models' potential of identifying disease-relevant traits indicating strong confidence and applicability among the agricultural sectors. In this work, they contribute to bridging the gap between deploying conceptually efficient Deep Learning AI models and their functional deployment to promote precision agriculture.

Keywords: ***CNN (Convolutional Neural Network), Explainable Artificial Intelligence (XAI), Deep Learning Interpretability, LIME, Grad-CAM ++, ResNet-50, MobileNetV2, Precision Agriculture.***

1. INTRODUCTION

Agriculture is considered one of the basic building blocks of food security around the world, and among all, corn is one of the most widespread crops in every continent. This crop faces significant yield losses due to severe diseases like blight, common rust, and grey leaf spot. Undiagnosed, these illnesses can result in significant drops in agricultural productivity and quality. This might cause significant financial losses, endangering global food security [1]. For any efficient treatment of crops, diagnosis at an early stage and with perfect accuracy is quite important. However, conventional diagnosis methods are always lengthy and involves manual efforts and massive work and bound to human error. Deep learning methods like Convolutional Neural Network have lately been showing a great impact on the detection and classification of diseases.[2] With increased deep learning models, how to represent interpretability or model explainability still seems a challenge, mainly concerning the stakeholders like farmers or agronomists for whom meaningful trustworthy predictions are necessary.

1.1. Research Question

How well and precisely Deep Learning models can be created for accurate classification of corn leaf diseases, and how can XAI techniques enhance model interpretability for better usability in agricultural diagnostics?

1.2. Research Objective

Technology in agriculture is not only creative but compulsory to ensure that we have food security and safe food for human consumption as population increases soon. As a result, this research seeks to establish a dynamic model with a view of identifying a system that can diagnose diseases such as common rust, blight, as well as grey leaf spot on corn plants and set apart from healthy corn plants.

The objective of this research is to develop deep learning model; ResNet50 and Mobile Net V2 for accurate corn leaf disease identification. Because of the 'black-box' characteristic of these models the author uses Explainable-AI strategies like LIME and Grad-CAM++ that show which parts of the images affect the choices. In this case, we will use these two XAI techniques for deep learning model with an aim of providing an interpretative and transparent manner of analysing the prediction ability of the deep learning model.

1.3. Research Gap Addressed

Classification is well accomplished with deep learning models, but their tendency to act as 'black boxes' has prevented their adoption. This research work adopts explainable AI techniques to interpret and validate predictions in the classification of plant diseases as very few studies have done this earlier. Since early disease detection and evidence-based decision making in the optimization of crop yields are central to precision agriculture, the proposed method will greatly influence this practice.

To give more specific details of the related work we carried out, methodology used and the overall experiment conducted for our work, the following sections presents a detailed overview of them all. We will also be making some explanation on Integration of XAI techniques and Developing trust in the end users also. The outcomes once again prove that it is possible to train deep learning state of art models with interpretability frameworks for entirely new kinds of agriculture diagnostics.

2. Related Work

Numerous studies have employed a variety of image processing techniques to categorize plant diseases using picture datasets from different sources. The relevant techniques employed by earlier research that can support or act as a guide for similar work on this research is discussed below.

2.1. Deep Learning Architectures & Disease Detection

Modern agriculture depends much on automated plant disease diagnostics as early and efficient identification helps to lower crop loss. Balavani, K et al., & Shankar et al. (2023) [3] underlined the shortcomings of the current method and recommended a powerful classification system using ResNet-50 design. Using skip connections and transfer learning, their study obtains a high validation accuracy of 99.3%. Its resolves significant gaps in the problem brought on by vanishing gradients and the inadequacy of earlier deep learning models for specific problems. But the important thing that this model lacks is the ability to explain the models' reasons behind the disease prediction. We will implement XAI techniques for model interpretability and explainability.

The study by Verma, D et al and Bordoloi, D et al (2021) [4] established a MobileNet V2 based deep learning model with the objective of ensuring that the model as a good balance between speed and accuracy. To address some of the challenges such as gradient vanishing and computing cost, their work exploits that fact that MobileNetV2 is specifically designed with depth separable convolutions and inverted residual linear bottlenecks. The accuracy of the models ranged 99.46% that is as good as other architectures such as InceptionV3. As today's state-of-art models like InceptionV3 or DenseNet cost a lot of computation power which makes them inapplicable or nearly impossible to implement within real-life application scenarios like mobile or even real time. However, the paper does not explore it under another perspective: i.e the decision-making process of the model. This makes be hard to comprehend how such models organize their outputs. This is vital and hence this aspect of explainability will be focused and applied in our current research.

An optimized DenseNet-based deep convolutional neural network (CNN) architecture for the recognition and classification of corn leaf diseases is proposed by Waheed, A. et al and Goyal, M. et al (2020) [5] The proposed model provided an accuracy of 98.06%, the number of parameters was only 0.0776 million, which is less than modern architectures such as EfficientNet (4.41 million) and VGG19 (20.18 million). It means less training time and overall power consumption and makes the developed model suitable for practice. The study fulfils significant research questions that are still open in today's AI and ML research domain; specifically, the high computational requirements and parameterization issues that exist with current CNN models while offering the ability to scale with large datasets. A few limitations were misclassification of diseases particularly when diseases have similar symptoms like Cercospora leaf spot and Northern leaf blight diseases. In our research we will improve such misclassification issues that were faced by this study

2.2. Integration of XAI Techniques for Enhanced Transparency

Rakesh, S. et al and Indiramma, M et al, (2022) [6] has proposed a novel approach in plant disease detection through the use of Explainable AI (XAI) methodologies which includes Grad-CAM and LIME together with deep learning architectures including ResNet and Inception V3. The model developed for ResNet attained 99.2% on the validation accuracy and Incepted V3 model 95.46% highlighting the system's ability to classify 38 diseases on 14 crops accurately. Thus, utilising XAI tools, the study presents visual interpretations of model predictions and key image features contributing to classification choices. This therefore enhances interpretability of deep learning models as well as helping users to build trust with Artificial intelligence products that make predictions. Some XAI methods such as Grad-CAM may be slowed down by a large computational cost preventing real time usage. The model performs well which is inspiring for our research. It focuses on 14 crops, but we will focus on

1 crop and go deeper in the analysis use the approach of transfer learning and light weight for model building to avoid computation overhead.

Wei, K., (2022) [7] aims to improve the interpretability and accuracy of deep learning models for classifying and distinguishing leaf diseases using attention mechanisms and interpretability methodologies. Using CBAM, integrated with ResNet architectures, the developed models demonstrated successful classification with accurate rates of 99.11%, 99.4%, and 99.89%, respectively. From the experiments implemented on ResNet50-CBAM, significant features like the texture and shape of the leaves were extracted efficiently. Contrasting the approaches, the study employed interpretability methods to ensure transparency to agricultural professionals and Grad-CAM as the most functional approaches among them provides clear visualizations some limitation of the above study is CBAM model requires high computation power and with the current research we can solve this issue by being computationally efficient as well as by using light weight model interpretability like LIME & implementing an advanced version of Grad CAM i.e. Grad-CAM++.

Nigar et al and Umar et al (2024) [1] carried out a study with the aim of developing an EfficientNetB0: Explainable AI (XAI) based system for identifying plant diseases. Its purpose is more definitive and straightforward: enhancing the accuracy, readability, and relevance to modern agricultural concerns of plant disease identification models. The model has impressive accuracy, precision and recall rate of 99.69%, 98.27% and 98.26% respectively out of 38 categories of plant diseases. The feature saves end-user credibility by applying Local Interpretable Model-Agnostic Explanation (LIME) to explain the model's reasoning to the end-users. Moreover, the effectively using the system for real life scenarios can be seen through the smartphone application called PlantCare which will supply farmers with useful information.

Batchuluun, G. et al, Nam, S. et al & Park, K. et al 2022 [8] proposes PlantDXAI, a plant and crop disease classification system that combines CNN and XAI tools including CAM. Their study reached the accuracy of 98.55% on the self-collected thermal plant dataset and 90.04% on the Paddy crop dataset. Because of the CAM integration, the model gives meaningful heat maps that point to the important areas in the image, which makes the model more helpful for agriculturists. Relatedly, the study presents a new thermal plant image dataset consisting of 4,720 images that expand the pool of accessible thermal images considerably. However, the environmental sensitivity of thermal imaging to factors such as humidity and temperature, dataset imbalance whereby some plants species or diseases may not be covered in the collected datasets, and increased computational power needed for the integration of CAM and discriminator nets.

2.3. Deep Learning Advancements for Plant Disease Detection

In the corresponding work of Chang, C. et al & Lai, C. et al (2024) [9] the approach adapts the confronting challenges of detecting potato leaf illnesses by using a lightweight deep learning model known as RegNetY-400MF that is designed for functioning under the limited resources circumstances. In the experiment, the model achieves 90.68% accuracy on a set of seven disease categories with the help of transfer learning and different data augmentation techniques. Cross-validation and data augmentation enhance the model's flexibility further, thereby enabling the model to handle a numerous revised environmental condition such as light conditions and obstacles. Some of the limitations of the study include imbalance of the datasets, and occasional misclassification of related characteristics such as fungi and pests. The current study will aim to solve these drawbacks including the ability of the lightweight model to explain the reasons behind its predictions.

Kumar, S. et al, Ratan, R. et al, & Desai, J.V. et al (2022) [10] have developed a lightweight and efficient cotton leaf disease detection system using TensorFlow and Convolutional Neural Networks (CNN) which will work in offline mode with iOS devices. They achieved it at 90% accuracy, and one super class namely Boll Rot, Fungal Leaf Spot and regular leaves were easy to distinguish. The model runs offline with the help of TensorFlow Lite and it benefits when there is poor internet connection typical for rural regions. Integrated in a standalone, native iOS mobile application with the utility of a simple interface, the presented system provides disease detection results as well as the appropriate pesticides for farmers to avoid crop loss and improve the quality of the crop yield. However, the research has also several limitations that should be discussed. The following are considered in this regard; first, the study only focuses on two diseases, second, the experimental results are evaluated on a dataset of 825 images and third, the authors propose the framework for iOS operating system which is disadvantageous to farmers who use Android operating system on their mobile devices.

Recent advances in machine learning and deep learning have brought-about key changes in plant disease detection as they address emergent concerns on efficiency, scalability, and accuracy. According to Shoaib, M. et al, & Shah, B. et al [11], the work of the authors appreciates that deep learning models especially CNN models are highly effective in, handling high resolution images and in detecting disease symptoms especially when evaluating state-of -the-art methods. Although such designs as ResNet, Inception, and DenseNet give high classification ability, it illustrates that even for the problem like data deficiency, augmentation techniques such as transfer learning or data augmentation can offer a reliable solution. However, the study has its limitations; for example, it relies on carefully chosen datasets, which may not capture the variability in the real world no scalability analysis of the method in other agricultural scenarios was conducted.

2.5. High level of Summary of the Literature Review

Authors	Year	Methodology	Findings
Balavani, K. et al	2023	ResNet-50, Transfer Learning	Obtained higher validation accuracy of 99.3%; solved vanishing gradient problem and scalability problem but lacked interpretability.
Verma, D. et al	2021	MobileNet V2	Obtained 99.46% accuracy; computationally lightweight with real-time applicability, however, the output lacked explainability and heavily dependent on the selection of datasets.
Waheed, A. et al	2022	DenseNet, Data Augmentation	98.06% accuracy; cuts down the amount of scale time and was able to prove scalability but occasionally the diseases are misclassified
Rakesh, S. et al	2022	ResNet, Inception V3, Grad-CAM, LIME	ResNet: 99.2% and Inception V3: 95.46%; was interpretably better with Grad-CAM and LIME but had computation overhead and was genre specific on XAI technique
Wei, K. et al	2022	CBAM, ResNet, Grad-CAM, LIME, SmoothGrad	They achieved more than 99 percent accuracy rate; improved black-box questions but witnessed high computational costs and dependency on many clean datasets.
Chang, C. et al	2024	RegNetY-400MF, Transfer Learning	90.68% accuracy; a flexible and light model, however, it was not evaluated concerning substantial applications, and had an imbalance of datasets.
Nigar, N. et al.	2024	EfficientNetB0, LIME	Constructed with 99.69% accuracy; LIME provided

			interpretability but required curated datasets and could not be scaled up.
Batchuluun, G. et al	2024	PlantDXAI, CNN, CAM	Got 98.55% (thermal dataset) and 90.04% (paddy crop dataset); gave explainable heatmaps but has problems of environment sensitivity, dataset imbalance, and time complexity.
Kumar, S. et al	2022	TensorFlow, CNN, TensorFlow Lite	An accuracy of 90%; offline usage on iOS devices though, it only supports two diseases, and the datasets are small which makes it unsuitable for Android.
Stadlhofer, A. et al.	2023	CNN, LIME, SHAP	SHAP offered consistent and detailed visualizations and has some drawbacks, that are the task-specific nature of the obtained visualization and high computational complexity.
Shoaib, M. et	2023	ResNet, DenseNet, Transfer Learning	Eliminated scalability and efficiency related issues but relied on specific and limited datasets
Hossain, M. et al	2023	ResNet-50, VGG-19, MobileNet-V2, Pre-processing	ResNet-50 achieved 99.53%, although it had more advanced pre-processing, the pre-processing was not stressfully tested, and it provided few comparisons on architecture.
Rashid, R. et al	2024	Multi-model Fusion Network, IoT, RL and PL Blocks	Obtained 99.23% detection accuracy; tested image plus environmental input but had computational and IoT dependency issues.
Tariq, M. et al	2024	VGG16, Layer-wise Relevance Propagation (LRP)	Testing was conducted with 94.67% accuracy; while interpretable heatmaps enhanced user trust the method struggled with dataset imbalance and was only moderately accurate relative to other available methods.

Table 1.1 High-level Summary of Related works

2.6. Conclusion

It is evident from the literature review that, deep learning, and Explainable AI (XAI) technologies have enhanced plant disease diagnosis without revealing some merits and demerits of using deep learning networks such as ResNet-50, DenseNet and MobileNetV2 get it right to classify the illnesses. MobileNetV2, RegNetY-400MF, and other models with low complexity were used for transfer learning and real-time calculating. Even to this present day, most of these models contain the "black box" nature of deep learning which makes users disregard them especially non-specialist agriculturalists.

What is required is a single and integrated model–high resource, such as the ResNet-50 and resource-scarce such as the MobileNetV2 coupled with XAI methods such as Grad-CAM++ and LIME. The present study addresses literature limitations: To enhance its effectiveness and to produce faster time-driven work, foster a numerically effective forecasting system. Thus, use XAI for transparency to assist in receiving the end-users' trust in the model. Enhanced pre-processing, hyper parameter tuning and augmentation programmes that have higher overall efficiency and can be applied to real conditions.

3. Methodology

The findings of this study will help agriculture experts classify different types of corn diseases and increase the effectiveness of treatment. Classification technologies produced using Deep Learning and Transfer Learning methodologies and tools may be advantageous to farmers and business stakeholders such as agriculture experts. This research project will thus employ the methodology known as CRISP-DM, which stands for "Cross-Industry Standard Process for Data Mining." The six steps of CRISP-DM, which are used in this research project, will be explained in this section.

3.1. Data Understanding

The data in this work, which was taken from publicly available repositories, comprises of maize or corn crop species of both healthy and diseased. It consists of approximately ~5000 images containing labelled images affected by diseases e.g., Blight, Common Rust, Gray Leaf Spot, and healthy leaves. Below are the few images from the dataset.

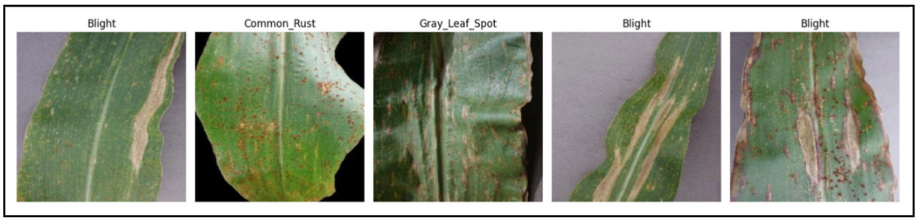


Fig 1.1 Original Dataset of Corn Leaf

3.2. Data Preparation

The data preparation process was completed by following the steps listed below.

3.2.1. Data Cleaning

The image dataset was obtained from sources on Kaggle. The produced dataset is consistent throughout the train and test folders in that it contains neither null nor missing values.

3.2.2. Exploratory Data Analysis

When there is uneven data, the classification model's performance decreases perhaps producing biased results or incorrect ratings. The Original datasets were divided into 70% training 20% validation & 10% testing using the pythons split folders package. For Resnet Model the Images were resized to 224x224 pixels to match the input size requirement of the model. Normalization was performed to scale pixel values between 0 and 1. When developing the model with Mobile Net V2, same pre-processing procedures were used, with a focus on lightweight data transformations to guarantee compatibility with the real-time focus of MobileNetV2. To maximize the model's input data, depth-wise normalization was also incorporated. The Model Architecture & flow is explained in depth in design specification section using **Fig 1.4.**

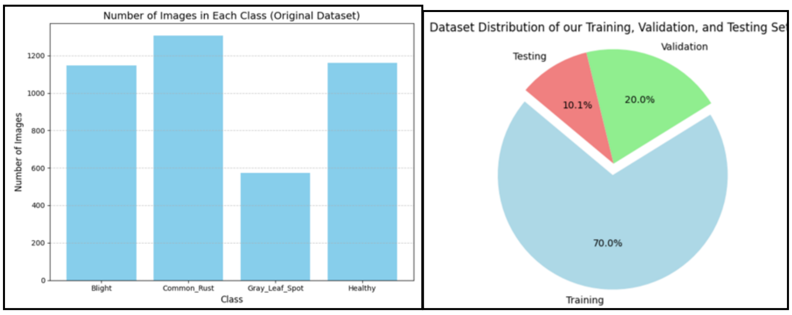


Fig 1.2 Class Distribution for Original dataset and Training, Validation & Testing datasets

3.2.3. Data Augmentation

Light variations such as shadows or low light can affect the pictures taken of corn leaves and may hide discoloration, rust, or spots in the image. Such images may make disease relevant details to disappear. Picture clicked from different angels may also confuse the model. To **deal with such issues**, we have applied **data augmentation techniques** that copies some of these environmental changes for instance, rotating, scaling, flipping, or adjusting brightness.

Fig 1.3 represents training set after data augmentation. Also, it was helpful to fix the problem of data imbalance since there were relatively few samples of class Gray Leaf Spot than the other classes.

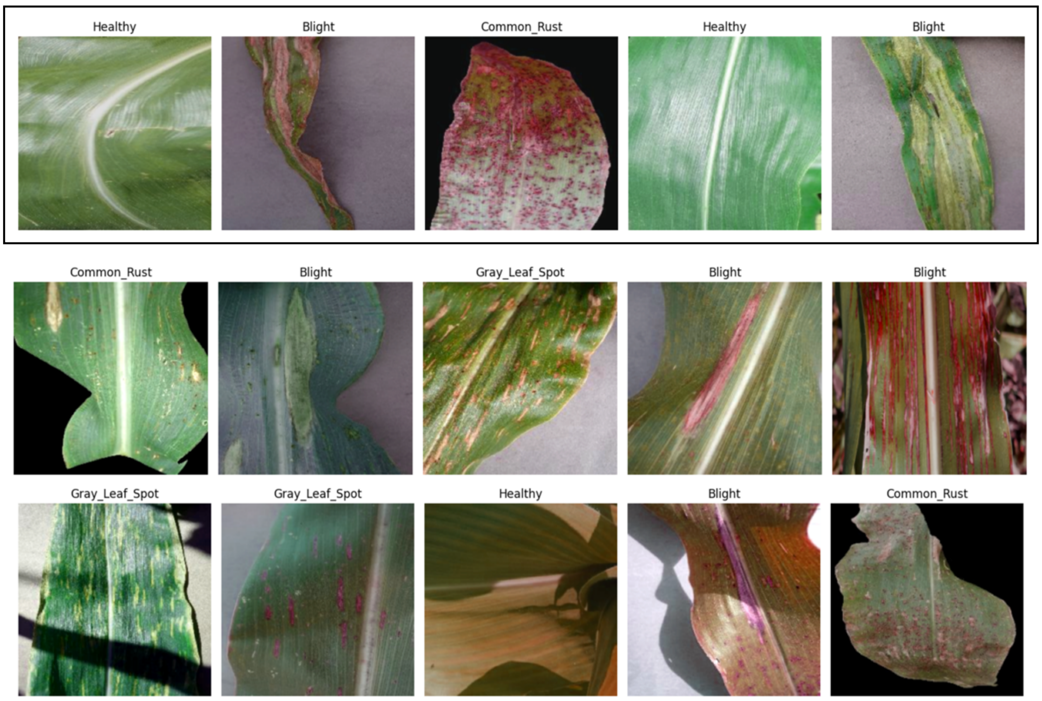


Fig 1.3 Images of Data Augmentation

This approach contributes to increased variability of the data and the ability to generate new data from a single image. The key idea of the increase of the size of the dataset is aimed at decreasing the overfitting risk. For data augmentation to occur, the ImageDataGenerator module was used. The changes included were normalizing brightness to range [0.5, 1.5] enhanced the model's ability to changes in lighting and angles. Zoom and Shear Transformations resemble weak image distortions brought about environmental factors for instance water droplets on the leaves causing a blur, set the width and height shift range to 0.2 at the input layer, rotation range of 40 degrees at the rotation layer which mimics the movement of leaves by wind or angles of natural growth and pixel values were rescaled by dividing with 255. Other options included to help diversify them were an additional 0.2 of shear range, 0.3 zoom range, and the flipping of both the x and y axis. To normalize the data appropriately, values of brightness have been transformed to the range [0.5, 1.5], and the feature wise center and scale was applied. If pixels are formed during transformations, then smooth interpolation was done using fill_mode parameter. The model adopted this strategy to overcome overfitting problems that supported the original dataset to enable generalization.

4. Design Specification

Figure 1.4 below highlights the process layout of the method used in this study, thus highlighting the mapped structure. The complete preprocessing and augmentation process were performed on the images before training which includes resizing, rescaling, rotating, flipping, and zooming, and shifting along width and height. Feature wise standard normalizing and brightness adjustments are also performed. The research uses transfer learning techniques like Resnet50 and MobileNetV2 for development of the model. GradCAM++ and LIME make sure that the interpretable outputs are open, and it also explains the reasons for the forecasts of the models. Based on disease classification that is supported by explanatory insights, the system is a potential solution for early disease diagnosis as well as for the applications of precision agriculture. The proposed process ensures that an optimal balance is achieved in activities related to the categorization of plant diseases and assuring excellent performances as well as interpretation.

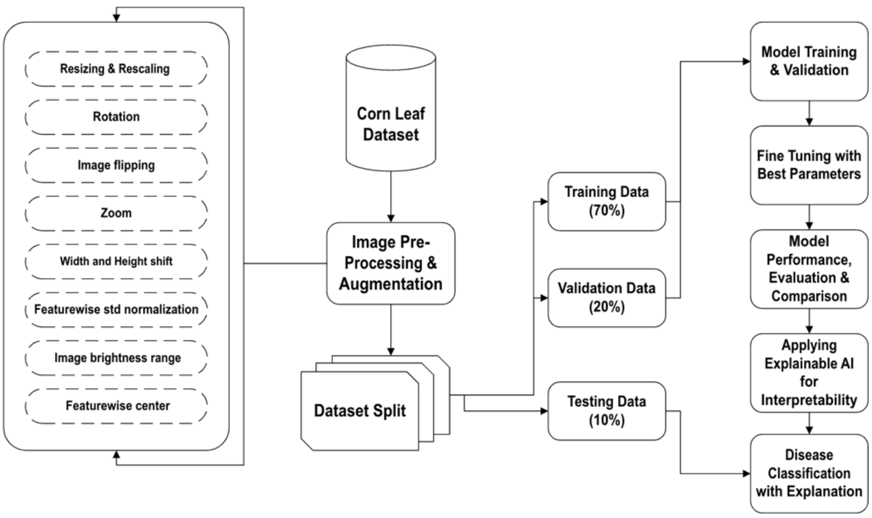


Fig 1.4 Design Specification for Corn Leaf Disease Classification using XAI.

5. Implementation

5.1. System Environment

We used Python 3.11.5 to develop the models, and Google Collab's Python notebook environment made it easy to run the corn disease classification models. Google Collab had ready-to-use libraries from Google, data was saved in Google Drive, and data, code execution, and results storage were organized. This system's simplicity, scalability, and GPU support for quicker model training guided its creation.

The implementation mostly relied on several different Python libraries and frameworks. Packages of foremost importance were TensorFlow & Pytorch useful in building & training the deep learning models, MobileNetV2 & ResNet50. For the visualizing the results and create plots we used Matplotlib and for the evaluation indices such as accuracy, precision, recall and F1-score we used Scikit-learn. Another Library such as NumPy and Pandas was employed in data manipulation and pre-processing. In the final stage, we deployed two pre trained architectures, ResNet-50 and MobileNetV2, and further modified these to optimize their performance.

Resnet-50 - ResNet-50 is based on residual learning that is, on a network made of residual blocks. These blocks let the network learn residual mappings instead of direct mappings, therefore enabling information to bypass some layers as needed. [18]

MobileNet V2 - The mobileNetV2 is a CNN architecture exploring how it operates on mobile devices. The structure is based on an inverted residual in which the residual links were between the bottleneck layers. Source of non-linearity is the use of lightweight depthwise convolutions in the intermediate expansion layer. Overall, MobileNetV2 has the first fully convolution layer with 32 filters and 19 residuals bottleneck layers.[19]

5.2. Model Training and Hyperparameter Tuning

The training process was divided into two phases, **initial training** with frozen layers and **fine-tuning** with the entire model.

In the **Initial phase** the base layers are frozen and only newly added layers are trained. This is done because the model will then focus on learning task-specific features from the current dataset without affecting the general features learned during pre-training on a larger dataset like ImageNet. The Pretrained models are already good at identifying the patterns from images. **Fine-Tuning the Entire Model:** Even though having the pretrained layers is helpful, the number of layers may not have the right features for the specific domain, for example disease-specific features on leaves. The adjustment can be performed on the feature extraction layers because the dataset will have some unique characteristics that the model needs to adapt. During this phase, all layers (including the pre-trained ones) are unfrozen and trained with a very low learning rate.
Resnet 50 - Originally trained for 25 epochs with the default learning rate and batch size, the model evaluated its baseline performance and pointed up areas needing work. The 25 epochs were chosen as the model started to overfit after 25 epochs. Extended training beyond this would cost more computational time as no growth were seen in the learning curves. Training histories made it possible to focus on the learning curves and observe the behavior of the model. After the first training, a hyperparameter grid search was run looking at various learning rates (e.g., 0.0001, 0.001, 0.01) and batch sizes (e.g., 16, 32). By applying the loops various combinations of learning rate and batch size we experimented to test and ensure we get the best possible combination. In Total we ran 3 (learning rates) × 2 (batch sizes) = 6 combinations. The model was trained for a fixed number of epochs (10), and the validation accuracy was recorded after each epoch. After training with each parameter combination, the final validation accuracy was used to find out the performance of the model. Retraining the model using the ideal configuration a learning rate of 0.0001 and a batch size of 16 produced enhanced accuracy and stability.

MobileNetV2- All layers in the MobileNetV2 baseline model were frozen during the first phase of training, thus their weights were not changed. This allowed the model to import feature extraction from ImageNet weights but train a new classification for the corn leaf disease dataset. The model trained for 50 epochs. There was fine-tuning for 25 more epochs, thereby totaling 75 epochs for training with lower learning rate of 0.0001. Fine-tuning was done with learning rate of 0.0001 for slow updates so to that to avoid forgetting of the pre-trained information.

5.3. Implementation of XAI Techniques & Its Justification

GradCam++: The Grad-CAM++ (Gradient weighted Class Activation Mapping++), which generates more interpretable heatmaps indicating which parts of an input picture are most important for the decision making. Grad-CAM++ proposes a more accurate way of performing weighted average based on second-order gradients. It is good for instance in allowing for a finer localization of some of the features of the system. In which an image has an overlaps or multiple objects, Grad-CAM++ can better highlight multiple contributing regions. Grad-CAM++ is better to handle multi region prediction compared to Grad-CAM. When spots or discoloration begin to appear on many leaf sections, plant disease categorization is important. Using Grad-CAM++, accurate multi class predictions for Blight, Common Rust, and Gray Leaf Spot in leaves are made. Finding which features in the leaf are important for disease categorization, Grad-CAM++ generates more precise and localized heatmaps, explaining the role of leaf texture, lesions, and rust spots [8] [17].

LIME: LIME is one of the explainable (XAI) techniques to produce human understandable explanations for the predictions of machine learning models. LIME is model agnostic, meaning it can theoretically explain the predictions of any machine learning model e.g. black box models such as neural networks, decision trees and so on, with no requirement to gain access to the internal workings of the model. We choose LIME because it is versatile and can deliver localized, model-agnostic explanations [1] [6] [7]. LIME may be used to any machine learning model, making it a strong tool to test ResNet50 and MobileNet V2 choices. LIME explains individual predictions by approximating the original model around input elements (e.g., picture areas) that influenced the model's conclusion. For corn leaf categorization, this helps identify diseased leaf patches. LIME highlights crucial areas or characteristics in simple, human-readable forms for simple owners or farmers or agronomists who trust AI solutions.

5.4. Justification for Deep learning Models Used.

The ResNet50 and MobileNetV2 models were selected for this work because of their shown performance in image classification challenges [3] [8]. Deep architecture with skip connections which solve the vanishing gradient issue and let deeper networks to be trained is well-known in ResNet50. This qualifies quite well for challenging classification tasks like corn disease detection. ResNet50 is known as to solve complex classification tasks and work efficiently as per our literature study. The study in our literature review by Balavani et al. (2023) [3] and they got the validation accuracy of 99.3% when using transfer learning through ResNet50 and also solving problems like vanishing gradients and scaling.
In our study, the ResNet50 model showed a high level of classification accuracy of 96.36% after fine-tuning, proving its ability to correctly classify samples even challenging samples in classes where they might look almost the same such as “Gray Leaf Spot” and “Blight”.

Conversely, MobileNetV2 was chosen for its lightweight design, which greatly lowers computational cost while preserving great accuracy by means of depth wise separable convolutions and inverted residual blocks. This is ideal for real-time applications on low resources devices [4] [9].

Model, such as DenseNet, InceptionV3, and EfficientNet, were first considered. DenseNet is a good performance in terms of feature propagation and its accuracy. However, it consumes a lot of memory to compute; hence is costly. InceptionV3 is equipped with an elaborate network with different sizes of the filter; however, real-time projects are thereby slowed down due to hardware demands. EfficientNet enhances the configurations in terms of accuracy and computational complexity while having more significant limitations concerning adaptation and utilization on target appliances [1][14][17]. The restrictions made the ResNet50 and MobileNetV2 models more appropriate for the parameters of this research.

The information from Table 1.2 was gather after carefully reading and comparing the literature work in our research by the authors Balavani et al. (2023) [3], Rakesh et al. (2022) [6], Verma D et al. (2021) [4], Rashid et al. (2024) [15], Tariq et al. (2024)[16] and Wei et al. (2022) [7].

Model	**Accuracy**	**Computational Efficiency**	**XAI compatibility**
ResNet-50	High	Moderate	Excellent
MobileNetV2	Moderate	High	Good
VGG16	High	Low	Moderate
InceptionV3	High	Low	Moderate

Table 1.2 Comparison of Models

6. Evaluation

Since no statistic may meet all model needs, various metrics are used to characterize model performance. In classification jobs, this part defines several measures and computes the most important metrics to understand the best model with exact predictions for larger-scale deployment. This part will focus especially on the ratings for accuracy, recall, f1 score & precision value.

6.1. Experiment 1: RESNET-50

The Resnet 50 Model was initially executed with 50 & 30 epochs since it was seen a overfitting issue after 25 epochs and no increase in accuracy curves the model was trained for 25 epochs

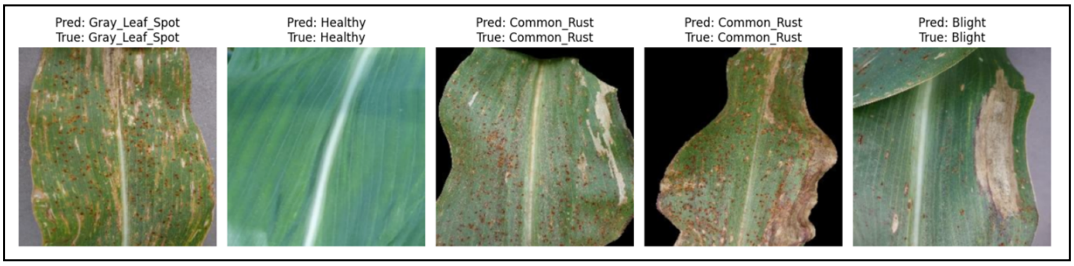


Fig 1.5 Results of Resnet-50 Prediction on Test Data Set

Initial Evaluation Before Hyperparameter Tuning: From the confusion matrix Fig 1.6, 127, 128 are correctly identified samples respectively; the confusion matrix further showed high accuracy of the model for classes as ‘Common Rust’ and ‘Healthy’. But 9 samples are misclassified as “Gray Leaf Spot” and another 3 as “Common Rust” for “Blight” and it has 106 correct samples identified. Likewise, the “Gray Leaf Spot” class has low performance of 56 right samples but 8 as “Blight.” This underscores the fact that at micro levels the model finds it hard in differentiating these two diseases. The author notes that these results may be perceived as the starting point from which performance can be increased.

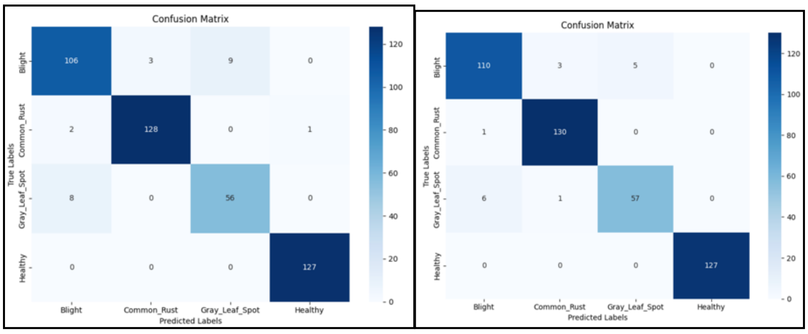


Fig 1.6 Confusion Matrix for Resnet-50 Before & After Hyperparameter Tuning.

After Hyperparameter Tuning: The "Blight" class has 110 correctly classified samples, with only minor misclassifications: 3 Common Rust and 5 Gray Leaf Spot. The “Common Rust” accurately predicts 130 samples with only one misclassified as “Blight”. From “Gray Leaf Spot” class it increased to 57 correct classification and 6 from it were misclassified as “Blight” and 1 as “Common Rust”. The model tested gives better performance than the pre-tuned model.

Learning Curves

Before Hyperparameter Tuning: Fig. 1.7 shows that training accuracy grows with epoch and reaches approximately 94%. This suggests that the present model matches the study's training data well enough to forecast accurately. Validation accuracy oscillates with generalization precision, causing significant swings. At some epochs, the curves climb to the training accuracy range, but the oscillations show the model's instability on fresh inputs.

Fig 1.7 Learning Curves for Resnet-50 Before Hyperparameter tuning.

Starting from epochs 1 to the last epoch, the training loss descends in values and thus the training is effectual, and the model does deliver good returns from the training data set. Especially in the latter stages, the high fluctuations of the validation loss indicate the subject matter might have been overtrained on the train set. The model will not be very useful if applied to the raw data.

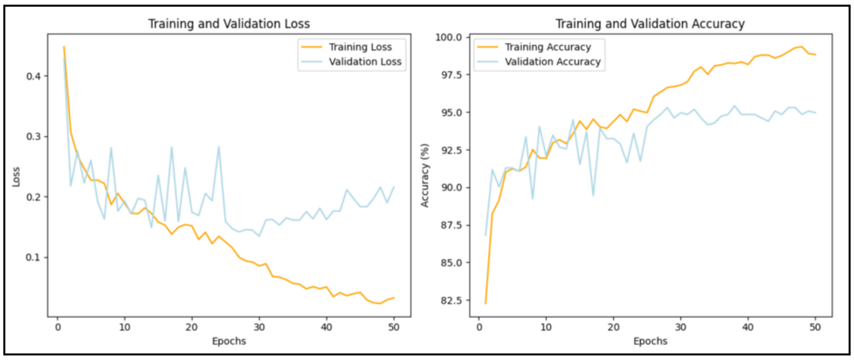


Fig 1.8 Learning Curves for Resnet-50 After Hyperparameter tuning.

After Hyperparameter Tuning: From Fig 1.8 validation loss is not very consistent in the initial epochs to reach a rhythm which shows that the model is learning along with generalization afterwards. Again, the validation accuracy jumps around in the first epochs, but from 25 epochs on, the validation accuracy is constant at about 95%. This means that the model of regression has good generalization ability to predict accurate values from unseen datasets, without overfitting. These results are clear indications that hyperparameter tuning is a sure way of enhancing the model's effectiveness. The low learning rate of 0.0001 ensured that weights were updated slowly to and did not overshoot optimal weights while a relatively high batch size of 16 ensured that gradients were updated commonly for stable learning.

6.1.1. Evaluation Metrics

Before Fine Tuning: This model gives an accuracy of 95% in generic classification which, though reliable, isn't the best for specific categories such as "Gray Leaf Spot." Originally, precision averaged at 0.94 with each class having above-average results, though slightly worse in terms of recall for the "Gray Leaf Spot" class; F1-score followed the trends of both metrics at 0.94. Weighted precision, recall, and F1-score are at 0.95; it learned more on familiar classes such as "Common Rust" and "Healthy."

	precision	recall	f1-score	support
Blight	0.91	0.90	0.91	118
Common_Rust	0.98	0.98	0.98	131
Gray_Leaf_Spot	0.86	0.88	0.87	64
Healthy	0.99	1.00	1.00	127
accuracy			0.95	440
macro avg	0.94	0.94	0.94	440
weighted avg	0.95	0.95	0.95	440

Fig 1.9 Classification Report for Resnet-50 Before Hyperparameter tuning.

	precision	recall	f1-score	support
Blight	0.94	0.93	0.94	118
Common_Rust	0.97	0.99	0.98	131
Gray_Leaf_Spot	0.92	0.89	0.90	64
Healthy	1.00	1.00	1.00	127
accuracy			0.96	440
macro avg	0.96	0.95	0.96	440
weighted avg	0.96	0.96	0.96	440

Precision: 94.02%
Recall: 93.22%
F1-Score: 93.62%
Accuracy: 96.36%

Fig 1.10 Classification Report for Resnet-50 After Hyperparameter tuning

After Fine Tuning: The proposed model gets overall accuracy of **96.36%,** which is greater than the results obtained using the pre-tuned model. Macro Average: Average precision equals 0.95 and average recall equals to 0.96 hence average of F1-score is also around 0.95 giving balance score to all classes. **Weighted Average:** For all three metrics, the weighted mean is 0.96 for precision, recall, and F1-score thanks to higher accuracy in classes that are better represented such as ‘Common Rust’ and ‘Healthy.’

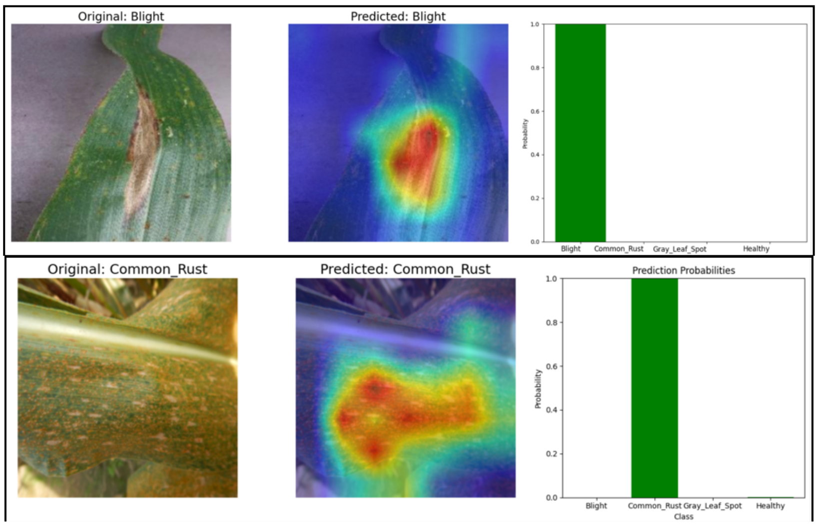
These results show how well fine-tuning hyperparameters like learning rate and batch size raises model performance. While the batch size of 16 gave a balance between gradient stability and computing efficiency, the learning rate of 0.0001 let the model converge gradually, hence avoiding overshooting ideal weights.

6.1.2. Applying Explainable AI in Resnet-50 Model

The **Grad-CAM++** heatmaps in Fig 1.11 show that the model can effectively spot significant leaf areas matching illness symptoms. These may be associated with the condition discoloration, patches, or odd texture. For instance: In the “Blight” prediction, the heatmap is pointed on the damaged, discolored area of the leaf which shows that our model can identify the features. In the case of “Common Rust,” the circled area provides the model’s properly selected aspect of the lesion on the leaf and its dependence on disease features.
From the heatmaps it is easy to infer that the model also has the distinction of distinguishing between diseases based on different discriminable features. For example: The heatmap of the “Gray Leaf Spot” shows multiple spot regions that identify scattered lesions inherent to the disease. The “Healthy” prediction is named so because it concentrates on the areas of the leaf which are not distorted in any way.

The bars represent the confidence values for the correct class closest to 100%, according to the model based on three selected samples. This leads to improvement of the ability of the model in determining the right disease of diagnosable diseases as expected if the wrong disease was diagnosed.
Validation of Model Learning: From the heatmaps we can also see that the model is paying attention at the right areas of the images and not the peripheral details. This supports the conclusion that the decision-making process of the model is to certain degree compatible with domain specific knowledge of plant diseases.

GradCAM++ Visualization



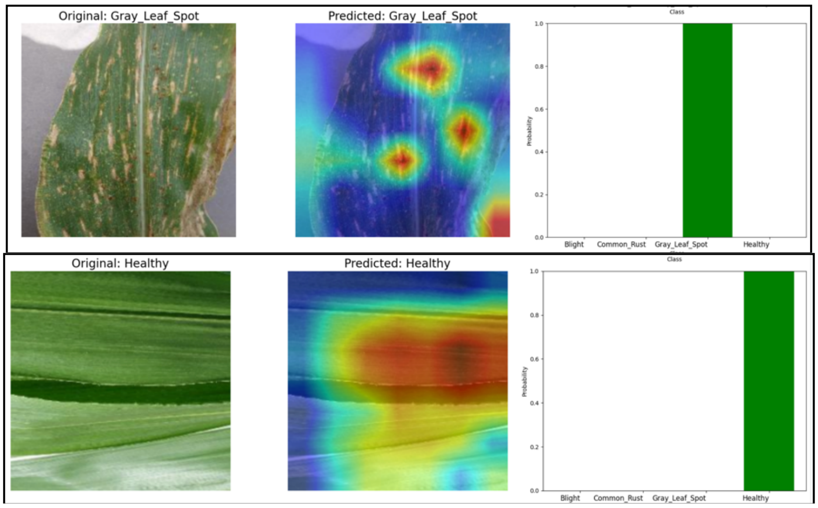
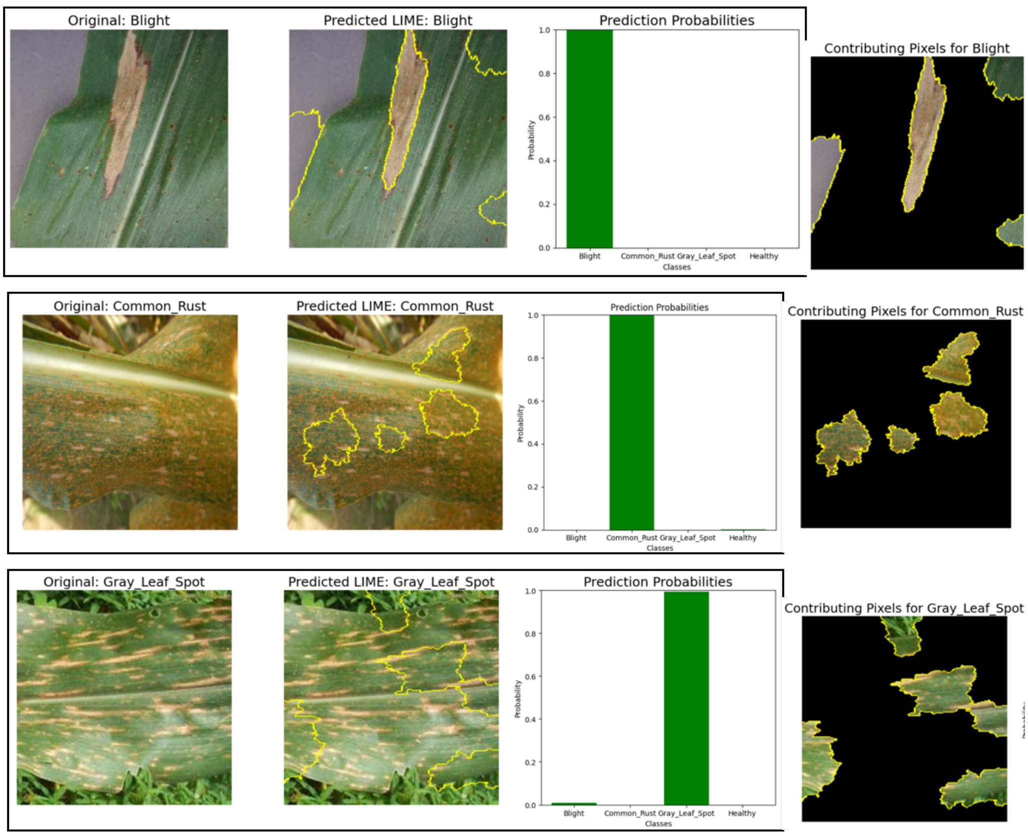


Fig 1.11 GradCAM ++ results for Resnet-50 Model

The **LIME** analysis of "Blight" In Fig 1.12 emphasizes the core damaged area of the leaf where lesions and discoloration abound. This shows the model has learnt to concentrate on the most important disease-relevant aspects. Characteristic of "Common Rust," the LIME output emphasizes several tiny, rust-like patches over the leaf surface. This confirms that the model can identify fine-grained characteristics suggestive of this condition. Typical symptoms of "Gray Leaf Spot," the LIME explanation points up scattered little patches and discolorations on the leaf. The focus on these areas shows that the model considers features different to this state. LIME focuses on the uniformity and continuity of ‘Healthy’ region hence there is no spot or blotch of imperfection.

LIME Visualization



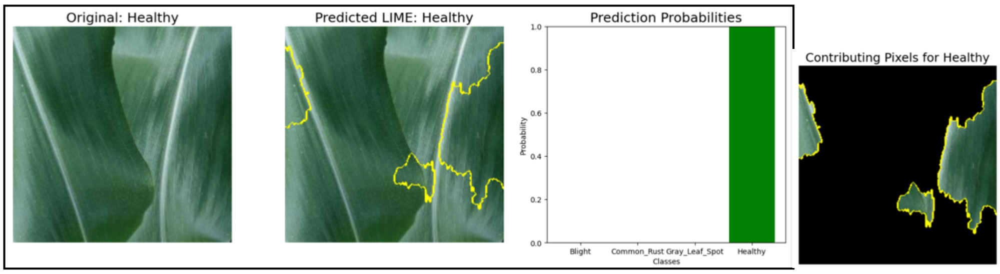


Fig 1.12 LIME Visualization for RESNET50

Overall Takeaways

Grad-CAM++ is interested in heatmaps that generally reveal larger areas associated with the disease on the leaf surface, blotches, or staining. LIME generated more detailed information because it works on feature-specific, low spatial areas of the image (like the lesions or spots). It is noticed from the yellow surrounds to certain features in the LIME outputs.

6.2. Experiment 2: MobileNet-V2

The Training data was increased from 70% to 80% to have more training data in this case as the accuracies and classification were very low initially.

Before Hyper Parameter Tuning: This model is pretty much comfortable while differentiating between "Common Rust and Healthy" category, further confirmation can be derived from high true positive results that are 243 and 218. Rates of misclassification of these categories remain negligible, meaning the model is effective in differentiating these diseases even before any attempts at tuning the model.

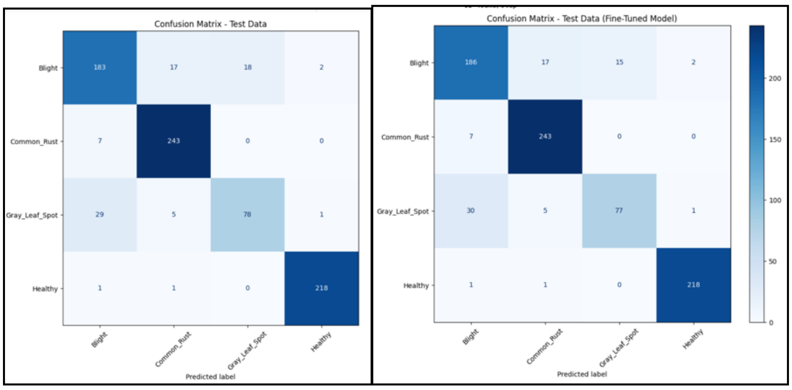


Fig 1.13 Confusion Matrix for MobileNet-V2 Before & After Hyperparameter Tuning.

One can observe high interclass confusion between the "Blight" and "Gray Leaf Spot" classes; for example, there are 29 pictures of "Gray Leaf Spot" mistaken for "Blight." he same can be observed for the "Gray Leaf Spot" category for which the overall misclassification errors are higher and only 78 samples in this case are classified correctly.

This means that the model tends to confuse diseases with closely related symptoms, features which could simply mean that there is inadequate sampling of features.

After Hyper Parameter Tuning: The "Blight" class is demonstrated to have a much-improved model, with the true positives rising from 183 to 186 and misclassifications reducing. However, even here, the minority of "Gray Leaf Spot" category still has relatively high misclassification errors, and therefore, other methods, such as advanced augmentation or attention mechanisms could be useful in improving performance in this case.

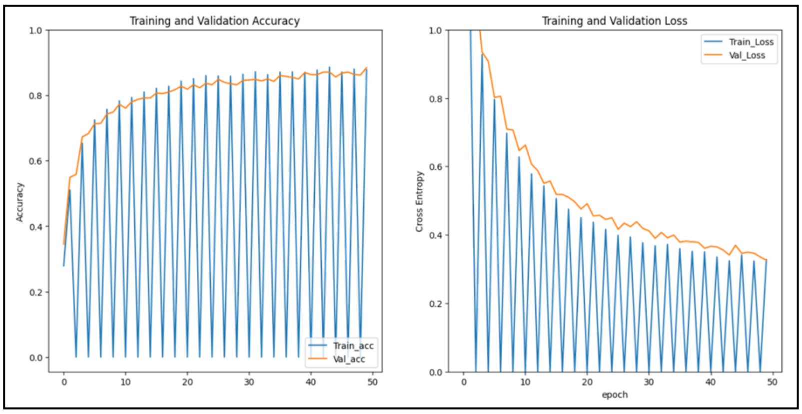


Fig 1.14 Learning Curves for MobileNetV2 Before Hyperparameter tuning.

Learning Curves

Before Fine-Tuning: Both training and validation accuracy are on the rise but oscillate, primarily for validation, due to overfitting or general instability.

In the loss curves, we observe a decreasing trend in the losses over epochs with a possibility of overfitting since the training loss is far smaller than the validation loss.

After Fine-Tuning: The training and validation accuracy get closer and get stable, while the validation accuracy increases and achieve a similar value to the training accuracy.

The loss curves eliminate high oscillations, and the difference between training and validation loss is more consistent, implying better generalization and model fine-tuning.

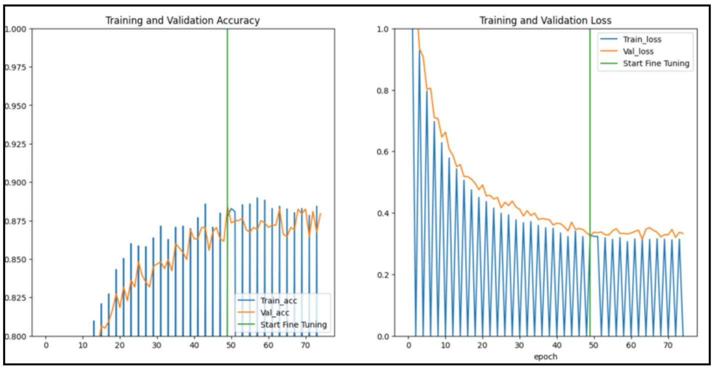


Fig 1.15 Learning Curves for MobileNetV2 Before Hyperparameter tuning.

6.2.1. Metrics

After Fine Tuning: The accuracy for the respective models cumulatively increased from 88% to 90,16%, which could be associated with an increase in the generality of the model. Precision and recall for "Blight' enhanced and F-score that was previously 0.83 enhanced to 0.84.

For "Common Rust" and "Healthy" categories, the performance is the same and is highly satisfactory with F1-scores of 0.94 and 0.99 respectively which proves the stability of our built classification model. The improvement for "Gray Leaf Spot" in precision (from 0.71 to

0.84) is slight while recall (0.68) is at the same level, and F1 score (0.75) also indicates that misclassification continues for this class.

Classification Report – Test Data (Fine-Tuned Model):

	precision	recall	f1-score	support
Blight	0.83	0.85	0.84	220
Common_Rust	0.91	0.97	0.94	250
Gray_Leaf_Spot	0.84	0.68	0.75	113
Healthy	0.99	0.99	0.99	220
accuracy			0.90	803
macro avg	0.89	0.87	0.88	803
weighted avg	0.90	0.90	0.90	803

Model Evaluation Metrics	
Accuracy:	90.162%
Precision:	89.994%
Recall:	90.162%
F1-Score:	89.936%

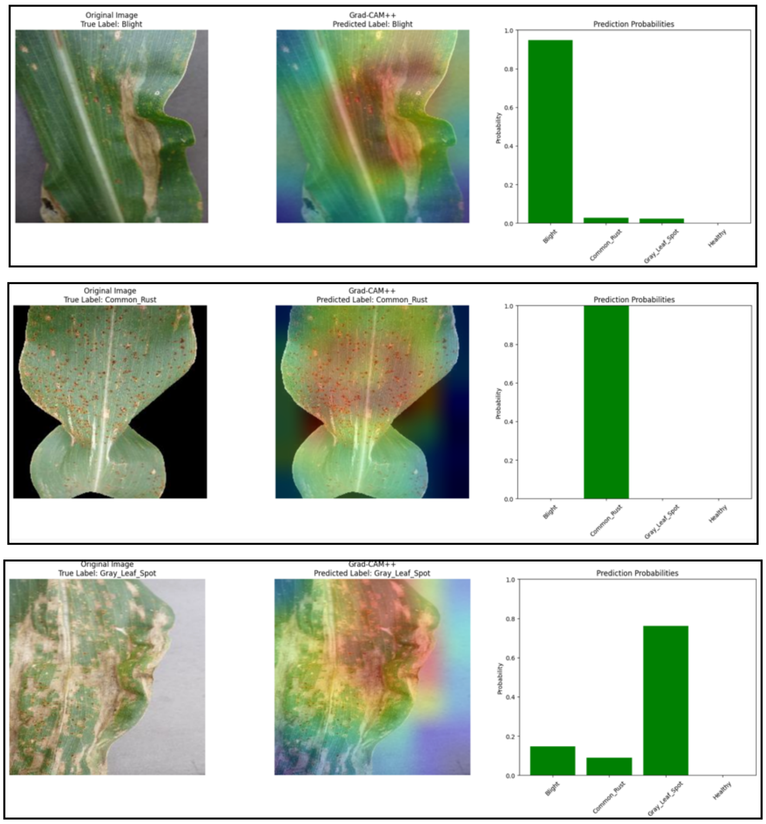
Fig 1.17 Classification Report for MobileNetV2 Before Hyperparameter tuning.

6.2.2. Applying Explainable AI in MobileNetV2 Model

GRADCAM ++ Visualizations: From 1.18 the heatmap, three regions of leaves are concerned for each case, illustrating how the features of the image are associated with the respective disease classes. If the model is wrong such as the "Gray Leaf Spot" class for the "Blight" image, Grad-CAM captures attention on areas that bear no similarity to the actual diseases.

LIME Visualizations: These results further support the utility of LIME in making MobileNet-V2 predictions interpretable, but also show few weaknesses in handling the difference in symptoms to the point of blurry distinctions between sometimes close classes such as Grey Leaf Spot.

GradCAM++ Explanation



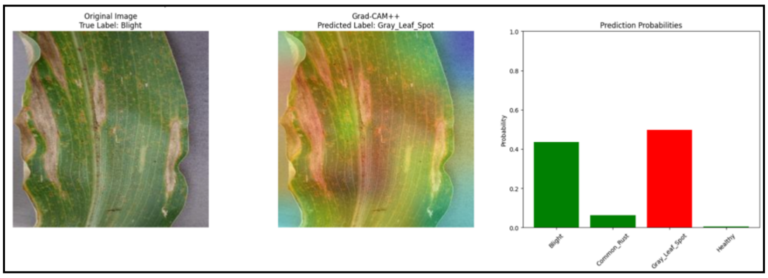


Fig 1.18 GradCAM ++ results MobileNet-V2

LIME Explanation

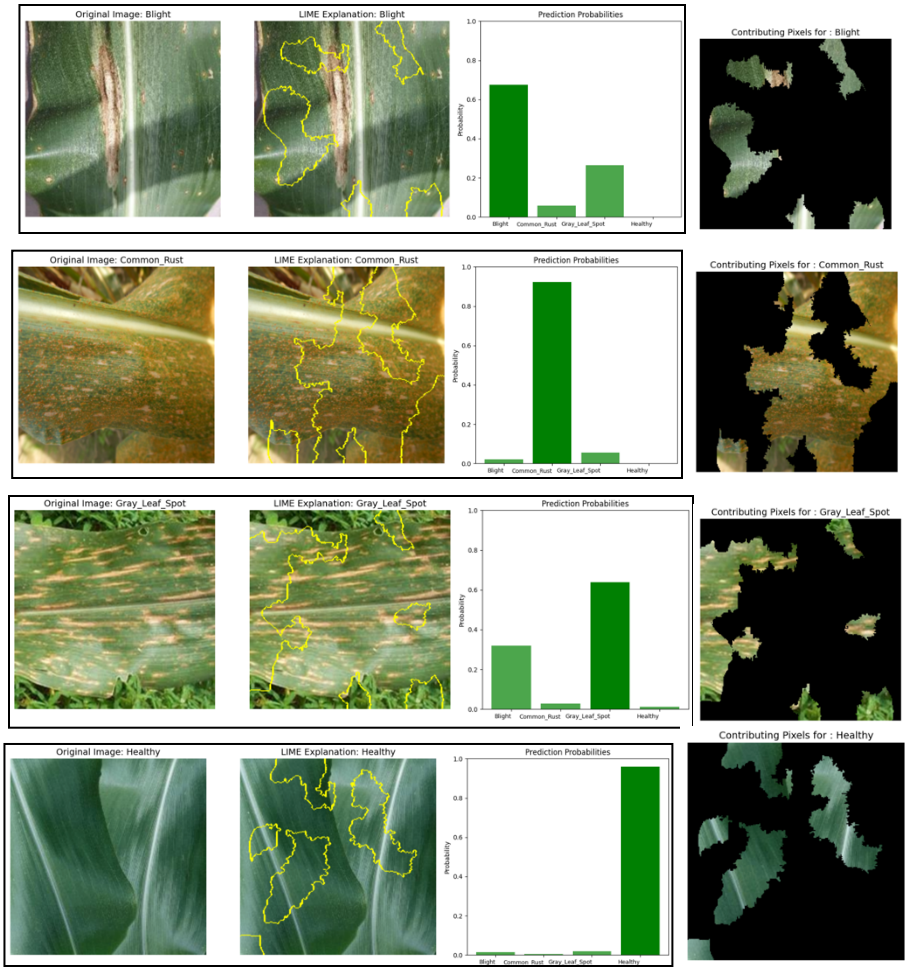


Fig 1.18 LIME results for MobileNet-V2 model & the contribution pixels

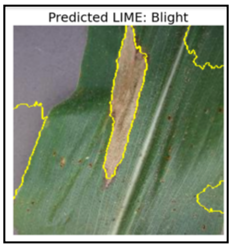
7. Discussion

7.1. Broader Implications of the Findings

This disease detection system enables farmers and other agricultural specialists identify diseases and embark on early measures that can prevent crop loss, optimize usage of pesticides, among other preventive measure to increase yields. Through use of XAI technologies, it is easy for the users to understand the decisions that the models make, therefore foster understanding and acceptance of the farm AI tools.

7.2. Critical Analysis

When working with both the models Resnet-50 & MobileNet-V2 initially they attributed results of misclassifying for few test cases like Blight and Gray Leaf Spot, to the visual similarity of disease symptoms. To address this issue, the author tuned both the models, searched for appropriate learning rates and batch sizes, as well as applied more advanced data augmentation techniques. After Hyper parameter tuning **Resnet-50** performed well in classifying images with **96% accuracy**. Also, when the XAI techniques like **LIME** was applied it **provided better explanations** correctly **marking the boundaries** of the diseased parts as shown in the Fig 1.19. But **in the case of Grad Cam++** the heatmap for few images as shown in Fig 1.20 although the **prediction was accurate** it **didn't highlight correct pixels** during predictions for few images.



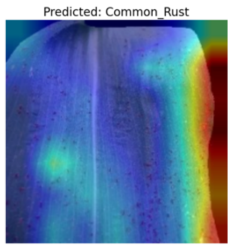


Fig 1.19 LIME Explanation **Fig 1.20 Grad CAM++ Explanation**

MobileNetV2 being lightweight even after fine tuning there were few misclassifications present with **accuracy of 90%.** This performance could be uplifted furthermore by adding extra steps of preprocessing like feature extraction, and giving more epochs of training which would probably increase the classification rate even more. The XAI techniques like **LIME & GradCAM++** was applied**,** it **provided better explanations and correct pixels** during predictions for almost all the images. In our results Grad-CAM++ accurately highlighted regions of the diseased leaves such as the lesions, rust spots, and discolorations and this was achievable even when there existed environmental factors which include lighting or the changes in angle. For example, it could still focus on rust patches in "Common Rust" or damaged areas in "Blight" under poor lighting or slight rotations. Under environmental conditions, such as shadows or partial occlusions, LIME allows the model to focus on specific disease-relevant regions, isolating these features from irrelevant background noise. This helps ensure that even subtle changes due to lighting or dust does not mislead the model.

Different corn leaf disease categories e.g., gray leaf spot, common rust, blights may exhibit unique patterns that affect how Grad-CAM++ and LIME explain the model's behavior. Heatmaps created by Grad-CAM++ focuses on vast areas related to symptoms of blight. They are also reliable for the identification of this disease because they highlight blotches and lesions found in Blight disease. LIME gives more detailed information about the damaged part where the lesions and discoloration exist in detail for blight.

Gray Leaf Spot poses more challenges for Grad-CAM++, as the heatmaps often overlap with features of other diseases, such as Blight. This leads to some difficulty in accurately distinguishing the disease in certain cases. Unlike LIME, which does a good job in this category offering more specific and precise explanations regarding some rare distinctly circled patterns and irregular brown blotches linked to Gray Leaf Spot.

Grad-CAM++ produces heatmaps that are accurate to the rust like patches observed on the surface of the leaf. Since small, circular spots representing this disease are highlighted, Grad-CAM++ is beneficial for representing both the general distribution and density of the rust.

LIME goes one step further in that it identifies these very specific, rust-like, granular areas in its explanations. One advantage that LIME has is that it shows individual regions that affect the prediction more clearly

This study fills the gap between very accurate deep learning models and interpretable AI solutions by situating these findings within the literature. ResNet-50, Mobile Net v2 and XAI in combination provide a scalable, affordable, and practical means of agricultural disease management and a roadmap for future smart farming technologies. To address the "black box" nature of deep learning models, Gradient CAM++ highlighted critical image regions influence prediction while LIME provides localized explanations.

As the prior research (by Rakesh et al., Wei et al.) employed explainable artificial intelligence techniques including Grad-CAM, this work expanded upon it by performing Grad-CAM++ an advanced version of it and LIME. It provided a better overview of what model interpretability actually means and detailed information about the pros and cons of models.

From the research and above discussion, the author interprets that the **Resnet-50 as the best model** in terms of accurately predicting between the disease classes and healthy corn leaves. And in terms of Model Explainability the **LIME performs better** with granular output in a way that will easily be understandable by farmers or agriculturists the reasons behind models' prediction.

Like previous studies, this research was faced by confusions between visually similar diseases (such as Gray Leaf Spot and Blight). But it tackled these difficulties by stressing explainability tools, something not seen as often across much previous research concentrating only on accuracy.

8. Conclusion

This work aimed to improve prediction performance and the explainability of decision-making procedures that deep learning models could offer through the investigation and improvement of accuracy and explanation. Our goal was to discover how using Explainable AI (XAI) approaches such as GradCAM++ and LIME can reduce the black box character of deep learning models while maintaining computational efficiency and accuracy of the model. This work achieved its goal of effectively proving via extensive testing that using fine tuning of ResNet-50 and MobileNetV2 models and implemented with XAI, they reach classification accuracy greater than 90% to 96%. Using Grad-CAM++ and LIME, interpretability was improved by providing perceptive representations of the important characteristics contributing to the predictions of the models.

However, these achievements still constitute some for our problems. Both models used well selected datasets which may be biased and to which the model was not exposed to all possible combinations of variables that the model could encounter in real world conditions.

8.1. Future studies and uses in Real World Context

Subsequently, a course for future studies will be to build an improved version of ResNet-50 with the characteristics of MobileNetV2 in terms of efficiency and real-time XAI. Another meaningful direction to expand this work lies in commercial research itself, such as electronic platforms, especially in the form of smartphone applications, or IoT-based agricultural control systems. The results provide a foundation for the development of user-friendly mobile apps for suggestions on illness diagnosis and treatment in practical environments. As an illustration: these models allow low power devices or the cloud to perform in real time illness diagnosis.

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