Incorporating Deep Features Extracted from Convolutional Neural Networks to Utilize Machine Learning Classifiers for Improved Identification of Maize Leaf Disease

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Declaration

It is hereby declared that

1. The thesis submitted is our own original work while completing degree at Brac University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. We have acknowledged all main sources of help.

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Dedication

We wholeheartedly dedicate this thesis to the unwavering pillars of our lives, our beloved parents, whose boundless support and encouragement have illuminated our academic journey, inspiring us to reach new heights. Our sincere appreciation goes out to our devoted supervisor and co-supervisor, whose counsel and insight have been crucial to the development of this research. This effort is dedicated, first and foremost, to the innumerable people whose lives have been affected by diabetic retinopathy and second, to the dedicated ophthalmologists who have worked diligently to better their patients' quality of life. Our research was conducted in the hopes that it would help improve their lives and the medical sector as a whole.

Ethic Statement

The authors of this thesis paper are well-versed in research ethics. We recognize the value of conducting research in an ethical manner while utilizing datasets, models and tools. There was no unethical behavior in the collection or use of the materials for this thesis. The datasets and images used in this study were obtained legally and with permission. Everyone's anonymity and personal data are now safe. We conducted an ethical and responsible study. We didn't let bias or competing interests get in the way. We were forthright in our reporting and we noted the caveats and unknowns in our investigation. We thought about the wider implications of our research and set out to make a positive impact on both human understanding and life. In order to minimize potential harm and maximize potential gain, we have taken the necessary precautions for our research. The work of others is recognized and cited inside our study. No dishonesty or plagiarism was committed on our part. We believe that all of the ethical requirements for this study have been met. Our efforts ought to expand human understanding and benefit society at large.

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Abstract

Maize is one of the most produced crops in the world and a significant contributor to the economy of various countries. Maize leaf diseases can lead to hamper of crop production and eventually reduce profit of agricultural farms. Through accurately identifying maize leaf disease earlier, farmers can take the necessary steps to minimize damages. In this paper, we propose to incorporate features extracted from deep convolutional neural networks and train them using machine learning classifiers for the identification of maize leaf diseases with high accuracy. For feature extraction, we trained 5 CNN models, which are InceptionResNetV2, DenseNet121, EfficientNetV2S, Xception and InceptionV3, reaching accuracy of 99.172%, 98.965%, 98.654%, 98.344% and 98.965%. Furthermore, the features extracted using these models were used to train K-Nearest Neighbors and Support Vector Classifier. The K-Nearest Neighbors classifier reach an accuracy of 99.586%, while the Support Vector Classifier reached an accuracy of 99.379%.

Keywords: *Maize; Corn; Crop; leaf disease; Accuracy; deep convolutional neural network; KNN; SVC*;

Chapter 1

Introduction

1.1 Background Study

Disease identification in maize, a crucial food staple worldwide, has become an urgent issue to farming. Maize's vulnerability to disease creates a serious problem for crop output and food safety. Conventional techniques of detection are notoriously time consuming and demanding of manpower. But in recent years, with the appearance of deep learning and Convolutional Neural Networks (CNNs), the field of maize disease detection has seen a revolutionary change. Models of corn disease detection systems built on convolutional neural networks (CNNs) have shown extraordinary performance with accuracy levels over 90%. These programs autonomously classify maize plant pictures as healthy or unhealthy using large, labelled datasets and deep learning techniques. This discovery has enormous potential for boosting agricultural output and guaranteeing food sustainability because it permits timely interventions and improved crop management practices.

When the financial toll of maize diseases is factored in, the significance of these developments becomes clear. In extreme cases, maize rusts such as common rust, southern rust and tropical rust can cause a 50% reduction in harvests. The devastating maize lethal necrosis disease has wreaked havoc around the world which resulted in output losses of 20% to 80%. During outbreaks, diseases like northern leaf blight and southern leaf blight can cut maize harvests by as much as 50%. There is an urgent need for the efficient and effective detection methods provided by deep learning and CNN-based models, as these diseases are responsible for billions of dollars in annual agricultural losses around the world.

1.2 Problem Statement

Despite the essential importance of maize production to global food security, it is threatened by a number of diseases that can result in severe reductions in crop yields. Detecting and treating diseases the old fashioned way is a tedious and time-consuming process. Recent breakthroughs in computer vision and deep learning have opened up a new era in the diagnosis and categorization of illnesses affecting maize leaves. The potential of these technologies, however, has yet to be completely realized because of numerous major obstacles.

1.3 Research Objectives

The purpose of the study is to detect maize leaf disease by examining images using models of both machine learning and deep learning. Corn has a high economic value and a wide range of benefits because it can be processed into food, industrial raw materials and a source of animal feed. The objectives of this paper include,

- To evaluate the current maize leaf disease diagnostic methods.
- To create a deep learning based model for detecting corn leaf disease at an early stage.
- Use the most recent CNN architectures in order to reduce error rates.
- To understand better CNN models and deep learning.
- Recognize the possibility of utilizing the CNN model for maize leaf disease detection.
- To efficiently combine both machine learning and deep learning and implement it.
- Aim to achieve the highest level of accuracy by model enhancement.

1.4 Research Orientation

In this paper, we have distributed our works into five different chapters where chapter 1 consists of an introduction and it's sections such as background study, problem statement, research objective and this research orientation part. The rest are chapter 2 literature review, chapter 3 research methodology, chapter 4 result analysis and chapter 5 conclusion respectively. In these chapters, we have studied numerous research papers related to our topic and explained the gist of those studies. Different types of models, results and outcomes are duly noted in our paper.

Chapter 2

Literature Review

In this paper [22], classifying maize leaf diseases with convolutional neural networks (CNNs) and Bayesian hyperparameter optimization is the topic of the work by Erik Lucas Da Rocha, Larissa Ferreira Rodrigues, and Jean-François Mari in the year 2020. Identifying the many diseases that endanger maize's quality and quantity is a time-consuming process, despite the importance of this crop to world food security [16]. This research evaluates three different CNN designs (AlexNet, ResNet-50, and SqueezeNet) to determine which is most suited for use in computer vision applications. Improvements in CNN performance are achieved by the use of Bayesian hyperparameter optimization, data augmentation, and fine-tuning procedures. CNNs were tested on the PlantVillage dataset, with remarkable results of 97% accuracy in diagnosing maize leaf diseases. The results are on par with or even better than those found in the literature on the subject. Hyperparameter adjustment is highlighted as a key factor in improving CNN performance, and the resulting models successfully retrieved key visual patterns associated with maize leaf diseases. As a result of using cross-validation, the findings are more solid and applicable to real-world situations. Furthermore, the study results indicate that the classifier system created is useful for farmers in effectively managing crop resources since it can accurately detect healthy leaves. In addition, breeders can use it to assess the incubation duration of a disease. The team hopes to use their method to categorize even more maize leaf diseases in the future, as well as investigate new optimization algorithms and methods for enriching their data. In light of the growing worldwide population and the associated agricultural issues, this study shows encouraging progress toward automating the identification and control of maize leaf diseases.

In this paper [29] the Study authors Hamish A. Craze, Nelishia Pillay, Fourie Joubert, and others asked in 2022, 'Deep Learning Diagnostics of Grey Leaf Spot in Maize under Mixed Disease Field Conditions', how challenging it is to detect the grey leaf spot (GLS) disease in maize when there are many different diseases present in the field images. They collected 18,656 photos, comprising examples from a variety of disease fields, to produce a massive dataset and then compared the performance of deep learning models trained on this data to that of models built on simulated data from places like PlantVillage. Based on their findings, a customized VGG16 network they dubbed 'GLS_net' achieved a remarkable 73.4% accuracy in binary GLS classification. However, it only achieved 72.6% accuracy when used in conjunction with MaskRCNN for leaf-background segmentation. Models trained just on PlantVillage data performed very well in lab conditions (94.1%) but poorly in the field (55.1%), highlighting the need for more realistic training data. GLS_net's flexibility was on full display when it was able to achieve 78.6% accuracy on photos from PlantVillage without having been trained on them. The discrepancy between its performance in the lab and in the real world was highlighted when it was applied to field photographs. This research demonstrates the significance of using real-world data to train deep learning models for improved disease diagnosis. Further investigation into background reduction strategies for use in field image analysis and picture databases is also suggested [12].

In the 2019 paper [19] 'Automated Leaf Disease Detection in Corn Species through Image Analysis', S. Praneetha and the Green Fields Klef team tackled a critical problem in plant disease detection within the context of Indian agriculture. More than half of India's workforce is employed in the agricultural sector, which accounts for a sizable portion of the country's gross domestic product. Diseases that attack plant leaves are a constant problem for India's agriculture yield. Because of their significance as early indicators of crop health, affecting both yield quantity and quality, the authors acknowledged the necessity of early identification and diagnosis of these diseases, particularly on leaves. To solve this serious problem, Praneetha and her colleagues recommended developing an automated system that could measure the level of infection on leaves, calculate the proportion of infected area and tell healthy leaves from diseased ones. Using a dataset obtained from Kaggle's Plant Village, they developed a method predicated on sophisticated picture analysis algorithms. They found the 3,852 photos of healthy and damaged maize leaves in this dataset to be an excellent training resource for their model. Image improvement methods were used in this study, with the CLAHE (Contrast Limited Adaptive Histogram Equalization) algorithm and clustering procedures taking center stage. They utilized the Keras sequential model, an effective machine learning framework for picture classification applications to determine whether or not individual leaves were healthy. The remarkable 91% accuracy rate they attained in their analyses only adds to the significance of their findings. The capacity to quickly detect and manage leaf diseases in maize crops with such a high degree of precision could prove invaluable to farmers. As stated in their 2019 paper, Praneetha and the Green Fields Klef team's research provides a promising answer to the problem of leaf disease detection in Indian agriculture. Their approach has the potential to significantly improve crop management through early disease identification and intervention, leading to higher agricultural yield and greater economic efficiency [19].

The authors of this study [18] recognized that crop diseases pose a serious risk to global food security and set out to investigate this phenomenon. In many parts of the world, limited infrastructure makes it difficult to detect these illnesses immediately. The researchers developed a deep convolutional neural network (CNN) based architecture, a reworked version of LeNet, to address this issue in maize leaf disease classification. Images of maize leaves from the PlantVillage dataset were used to test their method, which aimed to assign each image to one of four classes—three disease states and a healthy category. The study's primary conclusion was the exceptional accuracy (97.89%) achieved by their CNN model. This finding demonstrates the potential utility of their suggested method for speedy identification of maize leaf diseases, an important component of agricultural data. The primary objective of the study was to evaluate the performance of the LeNet architecture for automatically labeling photos of maize leaves based on the presence or absence of illness. The kernel size and number of convolutional layers were adjusted for this purpose. They conducted experiments and found that raising the network's depth helped boost accuracy. Genetic algorithms, support vector machines, and artificial neural networks were only a few of the techniques explored. The CNN framework they proposed worked well for identifying maize leaf diseases. In total, 4365 photos were used, comprising both healthy maize leaves and those affected by three of the most common illnesses that afflict maize. The study's most notable finding is that a kernel size of 3x3 effectively categorized maize leaf diseases. This demonstrates the significance of optimizing network parameters for optimal performance. They also highlighted how their CNN model may be used to categorize various plant leaf diseases, expanding its potential use in agricultural research. In conclusion, this research presented a strong CNN-based architecture for maize leaf disease classification, which achieved high precision. This study improved our understanding of how to optimize parameters and the extent to which the proposed strategy could be applied to other plant leaf diseases, which in turn enhanced our ability to ensure a steady supply of safe and nutritious food.

The research titles 'Maize leaf disease classification using convolutional neural networks and hyperparameter optimization' by Erik Lucas da Rocha, Larissa Ferreira Rodrigues and Joo Fernando Mari [22] describes the application of the CNN method to the identification and categorization of maize leaf diseases. When compared to other staple crops like rice and wheat, maize production is even higher. The rising demand for food is directly related to the accelerating rate at which the world's population is expanding. Therefore, anarchy will ensue if food, especially the primary food sources, becomes contaminated. As a result, a lot of work has gone into creating autonomous systems based on computer vision for identifying crop diseases. All of the photos are from the PlantVillage 1 dataset [12]. It includes 3852 photos of maize leaves, each showing a single leaf, sorted into four groups: healthy (1162), grey leaf spot (513), common rust (1192) and northern leaf blight (985).Coloured (RGB) images are converted to grayscale and the resulting grayscale images are scaled down to suit a fixed-size pixel, requiring further scaling of each individual pixel. 3 CNN architectures models were considered, including AlexNet [14], ResNet-50 [10], and SqueezeNet [11], with an accuracy of 97%, an average precision of 95% and an average f1 score of 96%. The main purpose of this work is to provide a method capable of classifying maize leaf disease images using CNNs enhanced by Bayesian hyperparameter optimization. As a result, the developed models have been able to extract crucial features about visual patterns of maize leaf and illnesses, suggesting that hyperparameter modification increased the performance of all examined CNNs.

Yanlei Xu , Bin Zhao, Yuting Zhai, Qingyuan Chen and Yang Zhou have stated in their paper that Infectious diseases pose a significant threat to maize, reducing both productivity and quality [1]. Disease identification in maize has traditionally been performed mostly through the manual expertise of agricultural specialists, an approach fraught with subjectivity and inaccuracy [30]. Progress in computer vision and machine learning, however, has opened the door to automated approaches to this issue [3–14]. This study by Maina and Njeri (2018) is an early example of the use of AI for identifying diseases in maize leaves. The team's method which prioritized colour feature extraction and made use of the backpropagation learning algorithm [24], resulted in a respectable accuracy of 78.94%. Gulhane et al. (2019) used self-organizing feature maps and backpropagation neural networks to identify cotton illnesses predominantly using colour features [37]. The literature shows a move towards more advanced deep learning approaches which have proven their worth across several domains [34], [23], [32]. It is noteworthy that Dawei et al.'s (2020) pest identification and detection system, built on transfer learning, achieved a recognition accuracy of 93.84% [23]. As a follow-up to these discoveries, Tian et al. (2021) demonstrated the utility of convolutional neural networks (CNNs) in maize disease recognition has attained a remarkable accuracy of 96.8 percent [32]. While these techniques show promise, it is clear that they frequently fail under realistic, complex conditions, when noise and interference from other sources are common [32]. The current study offers a new model called TCI-ALEXN that makes use of the AlexNet architecture to get around these restrictions. Based on previous studies [25], this model uses a novel convolutional layer and an Inception module. Overfitting issues caused by an abundance of parameters are also greatly reduced thanks to the substitution of a global pooling layer for the more common fully-connected layer. Furthermore, transfer learning techniques are skillfully used to leverage pre-trained models and increase learning rates in situations with insufficient training data. It is claimed in this study that TCI-ALEXN provides a promising path toward improving maize disease recognition accuracy, one that goes beyond conventional machine learning techniques and even outperforms earlier deep learning models such as VGGNet-16, DenseNet, ResNet-50 and the original AlexNet architecture [34].

In paper of Junde Chen, Wenhua Wang, Defu Zhang, Adnan Zeb, Yaser Ahangari Nanehkaran it is stated that, early detection of plant diseases, especially in maize, is crucial for reducing the negative impacts of crop diseases on productivity and quality which constitute a serious danger to global food security if left unchecked. New deep learning techniques, especially Convolutional Neural Networks (CNNs), have demonstrated exceptional effectiveness in picture recognition and classification. The authors suggest a new network architecture, dubbed Mobile-DANet, to help with this problem. It is tailored toward the detection of diseases in maize crops. Based on the DenseNet framework, this design keeps the same format for the transition layers but uses depth-separable convolution in place of the conventional convolution layers seen in dense blocks. In addition, the network incorporates an attention module that can recognize the value of inter-channel interactions and geographical elements in incoming data. Compared to deep CNNs, the computing requirements for training a model are reduced while accuracy is increased when transfer learning is used. The provided results prove that Mobile-DANet is useful. The model's accuracy of 98.50% on a publicly available maize dataset demonstrates it's reliability. When trained on a local dataset of maize crop illnesses, Mobile-DANet maintained a high average accuracy of 95.86% even when evaluated under difficult conditions with complicated backdrops. The importance of this effort is emphasized by projections showing that the world's population will rise to almost 9.7 billion within the next 30 years. It is necessary to limit crop damage, especially in staple crops like maize, which plays an important role in human and animal nutrition and different industrial applications, in order to satisfy the food demands of this expanding population. Identification of maize diseases has historically depended mainly on expert opinion and time-consuming field observations. This approach proved too time-consuming, expensive and unworkable for widespread use. New methods for identifying maize diseases, based on image processing and machine learning have arisen with the rise of digital cameras and processing power. The paper's literature review discusses the development of automated image recognition methods for diagnosing plant diseases. In classifying plant photos as healthy or unhealthy, these methods, which range from support vector machines (SVM) to artificial neural networks (ANN), have shown encouraging results [15]. For instance, the average accuracy of SVM-based methods for diagnosing maize illnesses was between 68.1% and 83.7%. The research also highlights the increasing significance of deep learning and CNNs in picture recognition and categorization. 2 notable examples are the 98.06% accuracy achieved by an optimized DenseNet architecture and the 97.89% accuracy achieved by a modified LeNet model in recognizing numerous maize leaf diseases. As a result of these achievements, deep CNNs are now widely recognized as the best approach to addressing difficulties in digital image processing for the identification of plant diseases. Despite these advances, the authors recognize the lack of diversity in previous research, particularly in picture datasets, which often consist of photos acquired in a lab rather than in real-world circumstances. Plant parts other than leaves, stems, and grains can be affected by crop diseases, making diagnosis more difficult. Mobile-DANet is a lightweight yet strong solution proposed by the authors to overcome these issues. Improved feature extraction, lower processing overhead and higher classification accuracy are all the results of Mobile-DANet's use of attention mechanisms and transfer learning. The authors also detail the data preprocessing procedures they employed to make the model more resilient such as image filtering, sharpening, scaling, edge filling, and data augmentation. The study includes in-depth analysis of Mobile-DANet's architecture, elaborating on it's decision to keep transition layers, replace depth-separable convolution and add attention modules [1]. These adjustments allow the model to accurately detect diseases in maize crops, regardless of the complexity of the environmental conditions. Notable in this work is the application of transfer learning, in which information learned in one context (the PlantVillage dataset) is used to train a model for a different context (identifying diseases in maize crops). This method takes advantage of existing models and streamlines the training process. Tables comparing Mobile-DANet's accuracy and performance against that of VGGNet-19, Inception V3, ResNet-50, DenseNet-121 and MobileNet-V2 are offered to illustrate the experimental findings. Mobile-DANet's average accuracy is 98.50% which is competitive.

This research, titled 'Use of Convolutional Neural Networks in the Diagnosis of Corn Diseases', addresses a major issue in agricultural science which is the precise diagnosis of illnesses that harm maize crops [27]. Disease diagnosis in agriculture has historically been based on the visual observations of seasoned farmers, which can introduce inaccuracies due to differences in perception [15]. Convolutional Neural Networks (CNNs) and other deep learning techniques are introduced in this research as a novel strategy to automating the identification of illnesses in maize plants which will help to alleviate some of the aforementioned difficulties. The devastating effects that crop diseases can have on food supply make this study all the more important [13]. Here the authors have stressed the need of diagnosing and controlling crop diseases in maize farming. It is widely acknowledged that crop diseases significantly reduce crop yields and economic output [15]. Since corn is sensitive to a wide range of pests and diseases across it's life cycle, severe output losses can occur if these problems are not resolved [13]. Diseases can vary in severity depending on latitude and growing season, thus correct diagnosis is essential for effective disease control [13]. In this study, an exploration about how to use machine learning and more especially deep learning, to overcome the difficulties of farmers' subjective visual observations and increase the speed with which diseases may be identified. The subject of machine learning deep learning [3] is emphasized for it's emphasis on the creation of learning computer programs. Deep learning which uses neural networks with several layers, has led to significant progress in many areas, the authors write [8]. This includes areas like speech recognition, image recognition, and text recognition. Also, CNNs are among the most regularly used models in the field of agricultural sciences where deep learning is being utilized to visually identify and classify plant diseases and pests. CNNs are multi-layered artificial neural networks optimized for image classification [17]. Their convolutional and pooling layers specialize in extracting features from images. The paper gives a comprehensive summary of the CNN architecture, describing its main parts in detail, including the convolution, pooling, flattening and fully-connected layers [9]. Moreover, the study acknowledges the difficulties of identifying plant diseases, such as the possibility of false positives due to indications of phytotoxicity or comparable leaf lesions. Traditional machine learning techniques such as Support Vector Machines (SVM) and K-means were used for plant disease categorization [5] before CNNs became popular. Various methods of image processing have been investigated in the past as well, such as image segmentation and color-based feature extraction [6], [4]. Although helpful, these methods weren't optimal for pinpoint precision. There is a lot of useful information on the dataset and the CNN network configurations utilized in four different scenarios [7] in the paper's methods section. Depending on the context and the data augmentation method used, the results show outstanding accuracy levels of 94.5 to 96.3% [20]. It's also worth noting that the CNN models converged well in a limited number of epochs, a sign of their efficacy in learning and identifying corn illnesses [20]. In order to further improve the tool's utility in optimizing crop disease management and increasing agricultural profitability, the paper also suggests future directions, such as applying the same approach to a broader range of corn diseases and plant data. This fits nicely with the current movement to apply AI and ML in agriculture in order to solve pressing problems.

This article presents a Deep Learning-based method for identifying maize crop illnesses with the goal of eliminating the subjectivity of conventional farmer observations. The study used a dataset of 3,852 photographs of maize leaves, which were sorted into four groups and they are, normal corn, corn with exserohilum leaf spot, corn with common corn rust and corn with cercosporiose [8]. They used Convolutional Neural Networks (CNN) to classify images and got a 94.5% success rate. Among the many factors that affect the quantity and quality of food available, plant diseases are often cited as a major contributor [2]. This study provides a helpful resource for boosting corn output through the precise detection and diagnosis of crop diseases. The convolution process is used across multiple layers in a CNN to determine what should be extracted from an image [9]. The most typical operation performed by the convolutive layers to minimize feature space is the subsampling or pooling layer but normalization and zero padding are also frequently used [13]. Image capture, image preprocessing, feature extraction and classification [20] were the four steps necessary to identify corn illnesses from photographs of their leaves.The paper's high rate of accuracy shows that it may be used to accurately identify and diagnose diseases.

Research published in 2020 found that a disease infecting maize plants caused a significant 622,403-ton decline in corn production in 2019, according to statistics from East Java's Badan Pusat Statistik [35]. After wheat and rice, corn is the third most important food crop worldwide [36]. In Indonesia, however, corn is only second to rice in terms of importance. According to this article, a drop in maize production was caused by growth problems, not disease attacks on corn plants. This disease can be fatal to maize plants if it is not caught and treated quickly enough [36]. The leaves, which are the first to show signs of the illness in maize, can be examined for yellowing and the appearance of spots in order to diagnose the problem at an early stage [21]. In this study, we use three different architectural models—AlexNet, LeNet, and MobileNet—to try to create a reliable model for disease diagnosis. Experts in agriculture determined that the collection included 4,188 photos classified as either "healthy," "with common rust," "with grey leaf spot," "with blight," or "with other diseases." The 4,000 photos were evenly divided into 20 percent training and 80 percent testing sets thanks to careful preprocessing of the data. When compared to AlexNet and LeNet, MobileNet fared better (83.37% accuracy). To perform deep learning, an artificial neural network design with many processing layers is employed [36]. When compared to other classification techniques, convolutional neural networks perform more favourably. CNN is often used for image recognition because of its superior accuracy compared to alternative deep learning methods [31]. In order to achieve statistical parity between the two groups, data augmentation is used to enrich the data of the minority group with information from the majority group [33]. The author argues that a larger dataset and larger input images would improve the model's performance even further.

Chapter 3

Research Methodology

The method employed in this research used deep features taken from Convolutional Neural Networks (CNNs) and machine learning classifiers to improve the identification of maize leaf diseases. An extensive dataset of maize leaf photos must be collected and preprocessed to ensure image uniformity and quality. High-level features were extracted from these images using pretrained CNN models which successfully captured subtle patterns and textures. Dimensionality reduction and feature selection methods were used to control the number of features. For the purposes of model building and evaluation, the dataset was partitioned into training, validation and testing sets. Different machine learning classifiers were explored, and their hyperparameters were tuned for maximum efficiency. To improve precision and reveal insights into model choices, researchers investigated ensemble methods and interpretability techniques.
An overview of the model architecture is presented in figure given below,

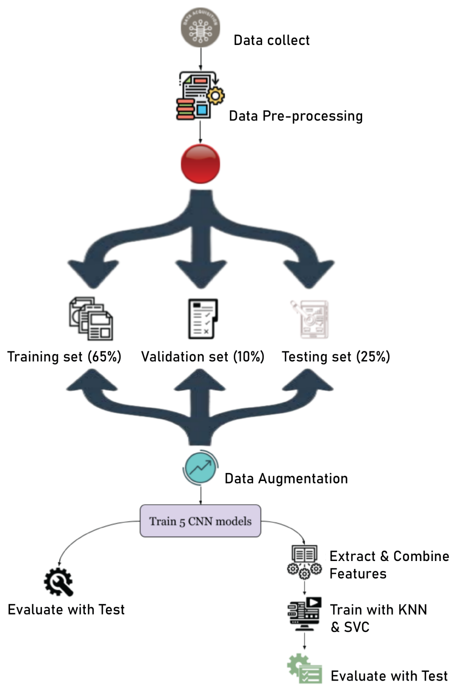

Figure 3.1: Flowchart of the proposed model.

3.1 Dataset description

We have acquired a dataset of 3,852 from plant village. It's divided into 4 categories of maize leaf states. The details about categories are given below,

Healthy: The leaves of a healthy corn plant are often a vibrant and consistent shade of green. Corn varieties will produce leaves with somewhat different hues but all of them will be uniformly bright green. A healthy corn leaf will have a smooth surface that is devoid of any lesions, growths or discolorations. There are no defects, like holes or tears. Those leaves are long and lance-shaped, with a strong midrib and a noticeable central vein. They resemble blades in that they taper to a point at the end.

Figure 3.2: An example of healthy leaf.

Common Rust: The fungal disease known as common rust primarily affects corn (maize) crops. Puccinia sorghi is the pathogen responsible for this. Although the leaves are the primary target of this disease, the stalks and husks of the maize plant are also susceptible. The optimal circumstances for the growth of common rust are high humidity and temperatures between 60 and 77 degrees Fahrenheit (15 and 25 degrees Celsius). The moisture from rain or dew on the leaves is what allows spores to germinate and the disease to progress.

Figure 3.3: An example of leaf with common rust.

Northern Leaf Blight (NLB): The fungal disease known as Northern Leaf Blight (NLB) is devastating to corn (maize) crops. Exserohilum turcicum, formerly known as Helminthosporium turcicum, is the causal agent of Northern Leaf Blight. This fungus only infects corn plants. Northern Leaf Blight is most easily identified by the symptoms it causes on maize leaves. Cigar-shaped lesions, with tan centres and dark brown or black edges, appear along the veins of infected leaves. These lesions are easily recognized because they are always oriented in a direction perpendicular to the leaf veins. As the disease advances, the lesions can grow, merge, and cover a sizable area of the leaf's surface. As a result of severe infections, leaves may die off and the plant may age prematurely, limiting photosynthesis and the quality of the corn ears that are harvested. Northern Leaf Blight favours hot and humid weather. Wind and rain can carry fungal spores, and temperatures between 68 and 77 degrees Fahrenheit (20 and 25 degrees Celsius) are ideal for infection.

Figure 3.4: An example of leaf with Northern leaf blight

Cercospora Leaf Spot (CLS) & Gray Leaf Spot (GLS): Common fungal diseases that attack corn (maize) plants include grey leaf spot (GLS) and cercospora leaf spot (CLS). The fungus Cercospora zeae-maydis is the primary culprit in chronic lyme disease.Corn leaves will develop tiny, brown spots that are either round or oval in shape. Yellow or tan dots with brown or reddish-brown borders are the first sign of these lesions. The lesions' centres turn greyish white as the condition advances and they could even join up to form larger irregular patches. Further, Cercospora zeina, a fungus, is responsible for GLS. It's lesions are typically rectangular in shape and greyish white in colour with a black border. Compared to CLS lesions, they tend to be thinner and longer. Leaves, husks and even stalks can all be affected by GLS lesions.

Figure 3.5: An example of leaf with cercospora leaf spot & gray leaf spot

3.1.1 Data Distribution Table (after oversampling)

Class	**Trained Images (2502)**	**Test Images (966)**	**Validation Images (384)**	**Total Images (4130)**
Cercospora Leaf Spot & Gray Leaf Spot	333	129	51	513
Common Rust	774	299	119	1192
Healthy	775	549	116	1440
Northern Leaf Blight	640	247	98	985

3.2 Validity and reliability of data

- **Data Validity:** Quality and correctness of the data used to train and test models are crucial to the reliability of results and by extension, the reliability of the research. Checking that the dataset is complete, broad and workable includes a wide range of disease types and stages with accurate labels.
- **Data Pre-Processing:** Make sure to document and adhere to best practices while performing data pre-processing tasks like data augmentation and splitting. The credibility of the findings increases with openness and transparency in data pre-processing.
- **Model Selection:** The appropriateness of the selected models (both deep learning and machine learning classifiers) should be explained and defended. Defend the models that's been used and how they helped reach the conclusions.
- **Evaluation Metrics:** Using proper evaluation metrics like accuracy, precision, recall and F1-score improves the trustworthiness of the model performance evaluation.

- **Cross-validation:** Results can be more trustworthy if cross-validation methods are used to ensure that models perform well when applied to data.

- **Experimental Design:** Design of experiments describe in detail the plan and execution of your experiments. This encompasses the process of fine-tuning hyperparameters, the methods used to train models and the presence or absence of any bias. The results will be more trustworthy if the experiment is well-designed.

- **Validation Set:** To avoid overfitting and improve model's generalization accuracy, it has been always recommended to employ a validation set alongside the training data.

- **Ethical Considerations:** When it comes to the ethics of research, it's important to make sure that both data collecting and model training procedures are up to snuff.

- **Future Work and Limitations:** Being honest about the things that couldn't be done with the data or the computing power that wasn't available. Giving some thought to potential biases and discussing how things may be made more trustworthy in the future.

3.3 Data Pre-processing

In order to train computers to identify maize diseases we first need to collect the necessary information. For our computer to learn efficiently, it's crucial that the data be in tip-top quality. In this section, we will examine the processes involved in making data ready for training a computer. Important because it sets the groundwork for the computer to learn and become adept at detecting diseases in maize plants. The steps we took to prepare our dataset are outlined below,

✓ **Data Splitting and Class Distribution:** The initial step involves dividing the dataset into three main portions such as training, validation and testing sets. This separation ensures that we have distinct subsets of images for training our model, evaluating it's performance during training, and conducting the final testing.

✓ **Class Counting and Balancing:** After splittation of data, the code counts how many images belong to each type of maize leaf disease in the training set. The goal here is to ensure that we have an approximately equal number of images representing each disease class. This helps prevent the model from favoring any specific disease.

✓ **Data Augmentation Functions:** Various image manipulation techniques are introduced, such as shifting, cropping, and rotating. These techniques are applied to the maize leaf images to create variations in appearance, simulating different angles and perspectives.

✓ **Data Augmentation Loop:** The code then goes through each disease class and determines how many augmented images are needed to balance the class distribution. This involves generating additional images by applying the previously mentioned augmentation techniques to images of underrepresented disease classes.

3.4 Description of models

EfficientNetV2S:

The EfficientNetV2 family of CNNs was developed with the goal of improving the speed and precision of common computer vision tasks. For mobile and edge devices where space and processing power are at a premium, EfficientNetV2S is one of several variations. By employing depth and breadth scaling to strike a good compromise between model size and performance, EfficientNetV2S stays true to the original EfficientNet design. A lightweight stem convolution layer is one of the main features of EfficientNetV2S which also includes bottleneck blocks to cut down on computational overhead and the addition of squeeze-and-excitation (SE) blocks to capture channel-wise dependencies and enhance feature representation.
The state-of-the-art methods used by EfficientNetV2S, such as stochastic depth and drop-path regularization, improve training stability and generalization. Furthermore, it has powerful attention processes built in to zero in quickly on important details in images. The remarkable performance of EfficientNetV2S can be further improved by applying model compression techniques like pruning and quantization. When it comes to image classification and object recognition on mobile and edge devices, EfficientNetV2S stands out as a state-of-the-art solution for contexts with limited resources[45].

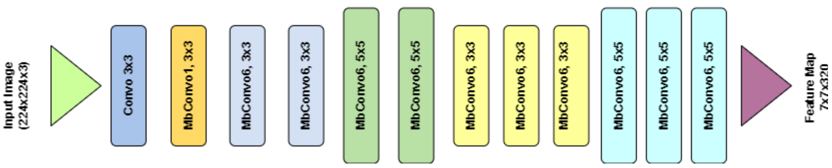

Figure 3.6: EfficientNetV2S model architecture.

DenseNet121

In the DenseConvNet, all of the layers are connected and share information with one another via feed-forward processing. For this purpose, it generates "Dense Blocks" that directly link together each layer. There are several convolutional layers in dense blocks. The formula for a dense block is as follows: Batch norm -> ReLu -> conv 3x3 -> Drop out. The input features are passed to the first convolutional layer, where they are transformed into additional features and then passed on to the second convolutional layer of dense block1. Concatenation is only possible if all of the feature maps are the same size. A transition layer is used to ensure that the feature map is consistent. Both the first dense block's output and the second dense block's transition layer output are fed into the second dense block. The layer of transition is made up of the following functions: Batch norm -> ReLu -> conv 1x1 -> Drop out -> pool 2x2. One connection exists between each layer in a standard

L-layer convolutional network. The feature maps produced by the layers below it are used as inputs by the layers above them, and vice versa. In addition to reducing the number of parameters and the vanishing-gradient problem, DenseNet improves feature propagation.

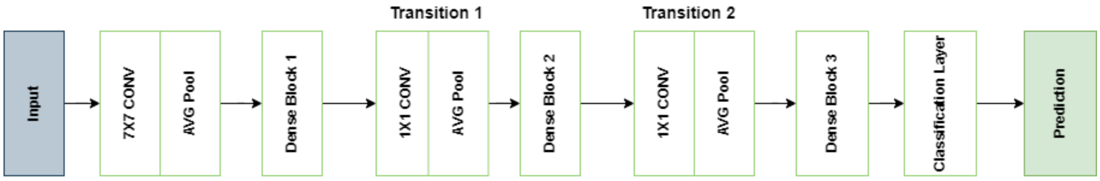

Figure 3.7: DenseNet121 model architecture.

Inception-V3

Modern deep convolutional neural network architecture Inception-v3, also known as GoogleNetV3, excels at picture categorization and object recognition. This model is well-known for its sophisticated feature extraction capabilities and is a big improvement over its predecessor Inception-v1.

The unique modules of Inception-v3's design use a variety of filter sizes, such as 1x1, 3x3 and 5x5 convolutions, in addition to pooling layers. The network's capacity to recognize complicated patterns in images is improved by the use of a wide range of filter sizes. To minimize the computational complexity of the network without losing any useful information, Inception-v3 also makes use of dimensionality reduction techniques such 1x1 convolutions.

In Inception-v3, auxiliary classifiers are utilized to overcome the vanishing gradient problem during training. Attached to the network's middle layers, these supplementary classifiers offer supplementary oversight during training. This helps with both speedier convergence and higher precision. In addition, Inception-v3 uses the network in network concept, which involves a global average pooling layer followed by fully linked layers to lessen the likelihood of over-fitting and increase the model's resistance to changes in input size. Faster training and improved generalizability are made possible by using batch normalization and ReLU activation functions uniformly across the network.

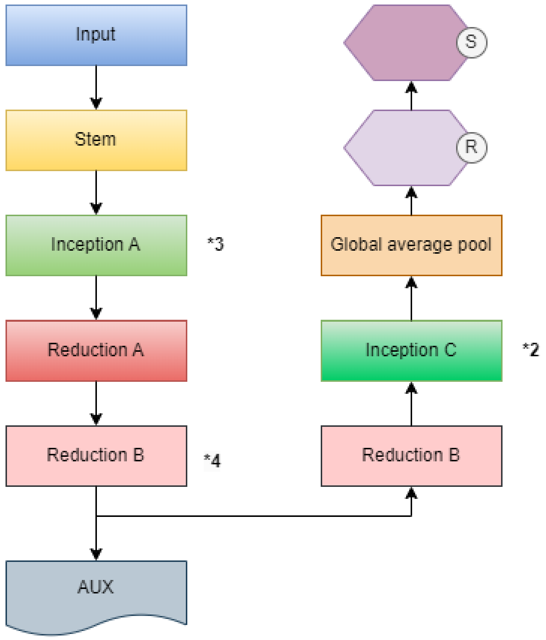

Figure 3.8: Inception-V3 model architecture.

InceptionResNetV2

The Inception-ResNetV2 design combines the best features of the Inception and ResNet deep convolutional neural network architectures. When it comes to picture categorization and other computer vision-related tasks, this architecture is unparalleled. To learn residual functions, Inception-ResNetV2 relies on the central idea of residual networks (ResNets), wherein the network is equipped with shortcut connections. These training-time shortcuts improve gradient flow, which reduces the impact of the vanishing gradient problem and paves the way for the development of extremely deep neural networks. The term ResNet is commonly used to refer to Inception-ResNetV2 because of its emphasis on including residual connections.
Taking cues from the original Inception design, Inception-ResNetV2 uses numerous simultaneous convolutional filters of varied sizes to capture characteristics across a range of scales. The combined effects of these filters enhance the network's capacity to acquire numerous features from the input data. Inception-ResNetV2 is distinguished by it's utilization of inception blocks connected by residual connections. The inception module is a part of these blocks which allows for the concurrent computation and concatenation of convolutions with varying kernel sizes. By allowing information to flow directly from one layer to the next, the remaining connections in these blocks improve the network's training and gradient propagation.

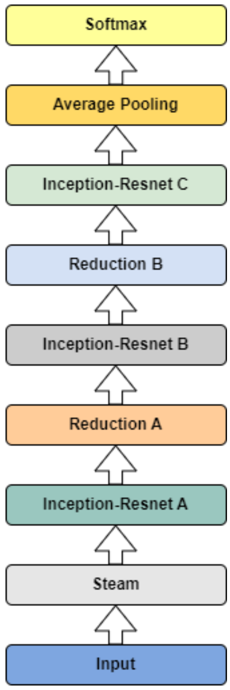

Figure 3.9: InceptionResNetV2 model architecture.

Xception

To effectively capture spatial and channel-wise relationships, the Xception CNN design uses depth-wise separable convolutions. Features similar to those found in Inception's modules, including depth-separable convolutions, linear bottlenecks, and residual connections that facilitate rapid feature discovery and rapid training convergence. Since it is completely convolutional, it can be used for a wide variety of applications, including but not limited to picture classification, object detection, and semantic segmentation. Xception is chosen for many computer vision uses because its pre-trained models allow for transfer learning and its design strikes a great balance between model size and performance. This is especially true in cases where computational resources are restricted.

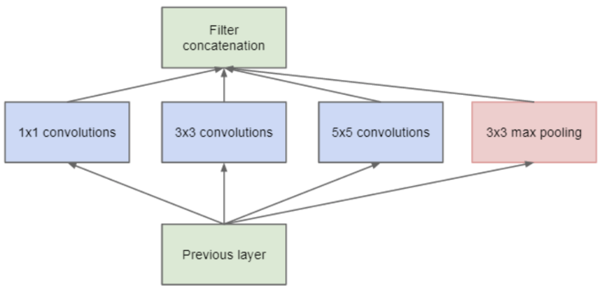

Figure 3.10: Xception model architecture.

K-Nearest Neighbours (KNN)

KNN is a supervised machine learning technique used for classification and regression that is both easy to implement and very accurate. To make predictions for a new data point, KNN looks for the 'k' nearest neighbours to that point in the feature space using a distance metric (e.g., Euclidean distance). In regression, KNN finds the average (or weighted average) of the target values of the k nearest neighbours, while in classification, it assigns the most common class among those neighbours to the new data point. Selecting a smaller value of 'k' makes the algorithm more sensitive to noise, while selecting a greater number may result in over-smoothed predictions. Since KNN is non-parametric, it can be used to a wide variety of datasets without making any presumptions about the underlying data distribution. However, it requires analyzing distances between the new data point and all of the previous data points in the training set during prediction, which can be computationally expensive, especially for large datasets.

Support Vector Classification (SVC)

Binary classification tasks, in which data points are divided into two groups are ideal applications for the machine learning method known as SVC. The key to how SVC works is that it determines the hyperplane that best divides the two classes by maximizing the gap between them. Support vectors or data points nearest to the decision border are what it uses to accomplish this. Linear, polynomial, radial basis function (RBF) and sigmoid kernels are just some examples of the kinds of kernel functions that can be used with SVC to tackle a wide variety of classification issues. Because of this adaptability, SVC can deal with non-linear relationships in data. SVC's resistance to overfitting also makes it a useful tool in other areas, such as image classification, text categorization and bioinformatics. Parameter adjustment is possible and it can be computationally expensive for large datasets.

3.5 Experimental Setup

In our experiment part i.e., the code section where we have built different functions and have taken different models for data training and testing the dataset.
In the 1st section of our code, we have imported the libraries that are required for different functions, models and calculations. However, the top classification layer of the base model is frozen. Then we have generated models by which we are going to train our dataset and they are DensNet121, InceptionResNetV2, EfficientNetV2S, Xception, InceptionV3, KNN and SVC. Also, we have taken image size (224 x 224), epoch (50), batch_size (32), rescale (image/255), adam_learing_rate was 0.0001 for first 20 epoch and for the rest 0.00001 (used adam as optimizer). We have used softmax as activation function. Further improvements will be made in order to make the models more efficient and to get better accuracy. Afterwards, we resized the images and their dimension in order to get a summary of our used models. From that we have got the results of total parameters, trainable parameters and non-trainable parameters. After that, we constructed the confusion matrix, model fit function for binary classification and compared the predictions of the model with the actual values from the training dataset. Last but not least, we have compiled models

and got accuracy percentages, as well as, the loss using the mentioned models.
Hardware configurations:
CPU: 12th gen Intel(R) Core(TM) i7-12700k
GPU: Nvidea GeForce RTX 3070 Ti

Chapter 4

Result Analysis

4.1 Preliminary Analysis

4.1.1 DenseNet121

For our first run of experimenting the convolutional neural networks, we ran the DenseNet121. It ran with a batch size of 32 and learning rate initially set to 0.0001 for 20 epochs then for 30 epochs we set the learning rate to 0.00001 using a scheduler function which is called during callback. So, for the 50 epochs, we ran the model after loading the weights of the model trained on the ImageNet dataset. After that we used Keras Checkpoint to save the model with the highest validation accuracy resulting in 0.9948. Moreover, to evaluate on the testing set we also used the best model. The model achieved an accuracy of 0.9896 on the evaluation of the model on the testing set. Figure 4.2 shows the training and validation losses of the model and Figure 4.1 shows the training and validation accuracies of the model's full training process. Moreover, we also showed the Precision, Recall and F1 scores of the models' testing set. Finally, we showed the confusion matrix of the model on testing set in Figure 4.3 for each classes.

Figure 4.1: DenseNet121 model's train and validation accuracy.

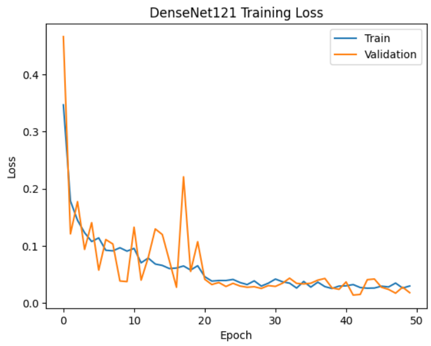

Figure 4.2: DenseNet121 model's train and validation loss.

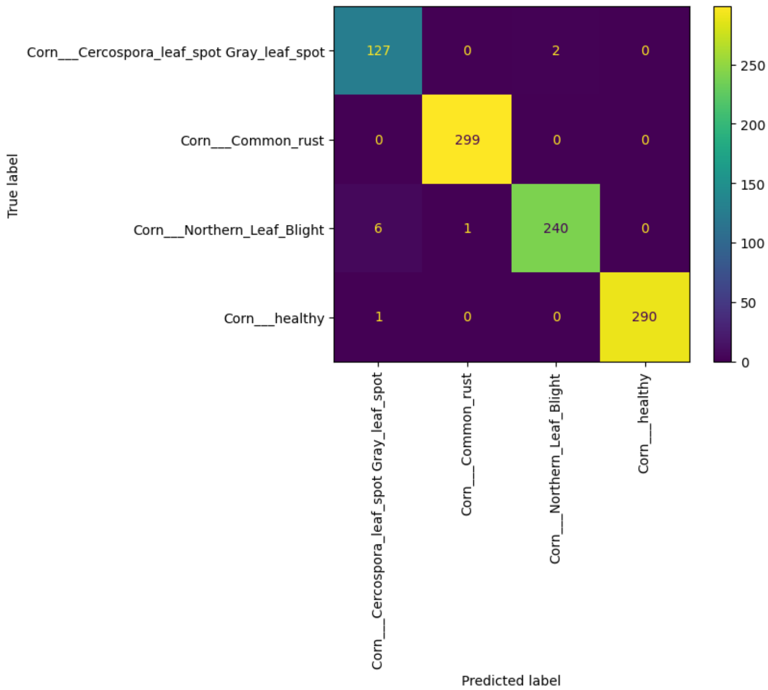

Figure 4.3: DenseNet121 model's Confusion Matrix.

Class	Precision	Recall	F1-score
Cercospora leaf spot & gray leaf spot	0.94776	0.98450	0.96578
Common Rust	0.99667	1.00000	0.99833
Northern Leaf Blight	0.99174	0.97166	0.98160
Healthy leaf	1.00000	0.99656	.99828

4.1.2 InceptionResNetV2

For the second run of experimenting with CNN model, we used the InceptionResNetV2. This model also ran with the same hyperparameters as the previous models. A batch size of 32 and learning rate initially set to 0.0001 for 20 epochs then for 30 epochs,the learning rate was changed to 0.00001 using a scheduler function which is called during callback. We again used Keras Checkpoint to save the model with the highest validation accuracy, this time resulting in 0.9922 which is a better then our previous CNN model InceptionV3. Then, the model achieved an accuracy of 0.99172 on the evaluation of the model on the testing set which is the highest accuracy so far amongst our CNN architectures. Figure 4.5 shows the training and validation losses of the model and Figure 4.4 shows the training and validation accuracies of the model's full training process. Moreover, we also showed the Precision, Recall and F1 scores of the models' testing set in table. Finally, we showed the confusion matrix of the model on testing set for each classes.

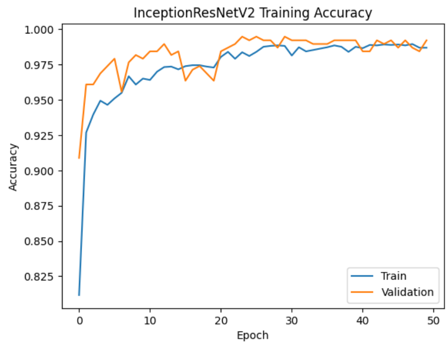

Figure 4.4: InceptionResNetV2 model's train and validation accuracy.

Figure 4.5: InceptionResNetV2 model's train and validation loss.

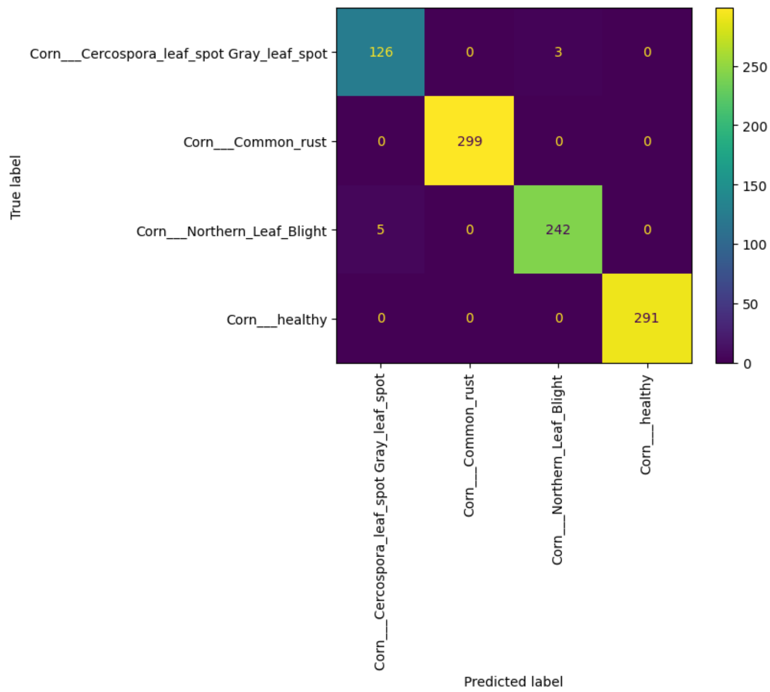

Figure 4.6: InceptionResNetV2 model's Confusion Matrix.

Class	**Precision**	**Recall**	**F1-score**
Cercospora leaf spot & gray leaf spot	0.96183	0.97674	0.96923
Common Rust	1.00000	1.00000	1.00000
Northern Leaf Blight	0.98776	0.97976	0.98374
Healthy leaf	1.00000	1.00000	1.00000

4.1.3 InceptionV3

For the third run of experimenting with CNN model, we used the InceptionV3. It ran with the same hyperparameters as the previous models. A batch size of 32 and learning rate initially set to 0.0001 for 20 epochs then for 30 epochs we set the learning rate to 0.00001 using a scheduler function which is called during callback. We similarly used Keras Checkpoint to save the model with the highest validation accuracy, this time resulting in 0.9870 falling behind DenseNet121. Then, the model achieved an accuracy of 0.98965 on the evaluation of the model on the testing set Which is the same as our previous CNN architecture. Figure 4.8 shows the training and validation losses of the model and Figure 4.7 shows the training and validation accuracies of the model's full training process. Moreover, we also showed the Precision, Recall and F1 scores of the models' testing set in table. Finally, we showed the confusion matrix of the model on testing set in Figure 4.9 for each classes.

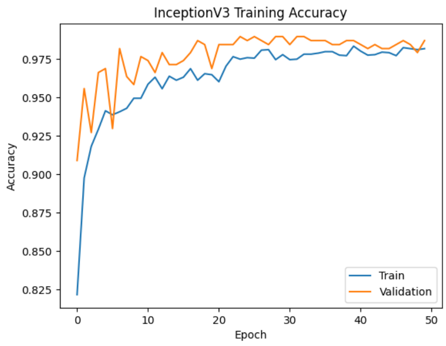

Figure 4.7: Inception-V3 model's train and validation accuracy.

Figure 4.8: Inception-V3 model's train and validation loss.

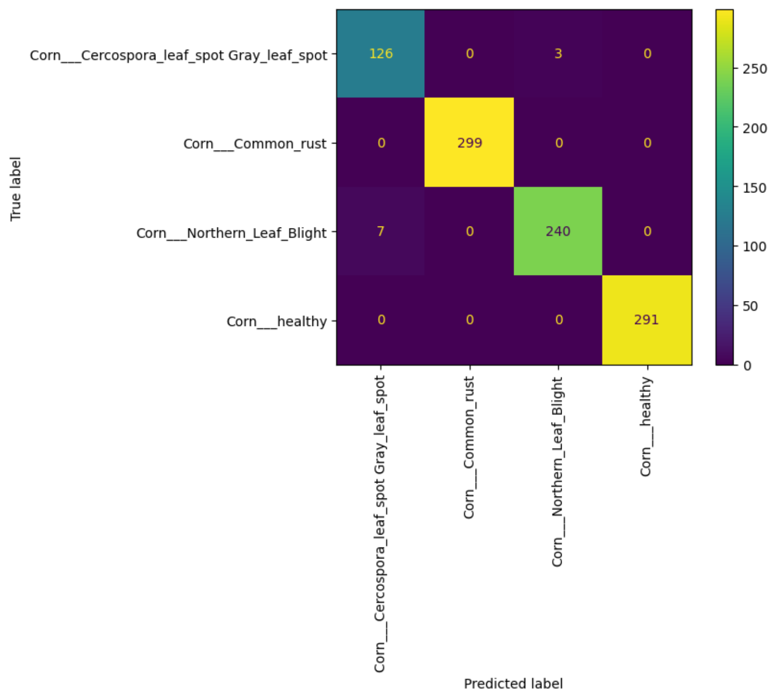

Figure 4.9: Inception-V3 model's Confusion Matrix.

Class	Precision	Recall	F1-score
Cercospora leaf spot & gray leaf spot	0.94737	0.97674	0.96183
Common Rust	1.00000	1.00000	1.00000
Northern Leaf Blight	0.98765	0.97166	0.97959
Healthy leaf	1.00000	1.00000	1.00000

4.1.4 Xception

For our fourth run of experimenting with convolutional neural networks, we ran the Xception model. It ran with a batch size of 32 and learning rate initially set to 0.0001 for 20 epochs, then for 30 epochs we set the learning rate to 0.00001 using a scheduler function which is called during callback. So, for the 50 epochs, we ran the model after loading the weights of the model trained on the ImageNet dataset. After that, we used Keras Checkpoint to save the model with the highest validation accuracy resulting in 0.9896. Moreover, to evaluate on the testing set we also used the best model. The model achieved an accuracy of 0.9834 on the evaluation of the model on the testing set. Figure 4.11 shows the training and validation losses of the model, and Figure 4.10 shows the training and validation accuracies of the model's full training process. Moreover, we also showed the Precision, Recall, and F1 scores of the model's testing set. Finally, we showed the confusion matrix of the model on the testing set in Figure 4.12 for each class.

Figure 4.10: Xception model's train and validation accuracy.

Figure 4.11: Xception model's train and validation loss.

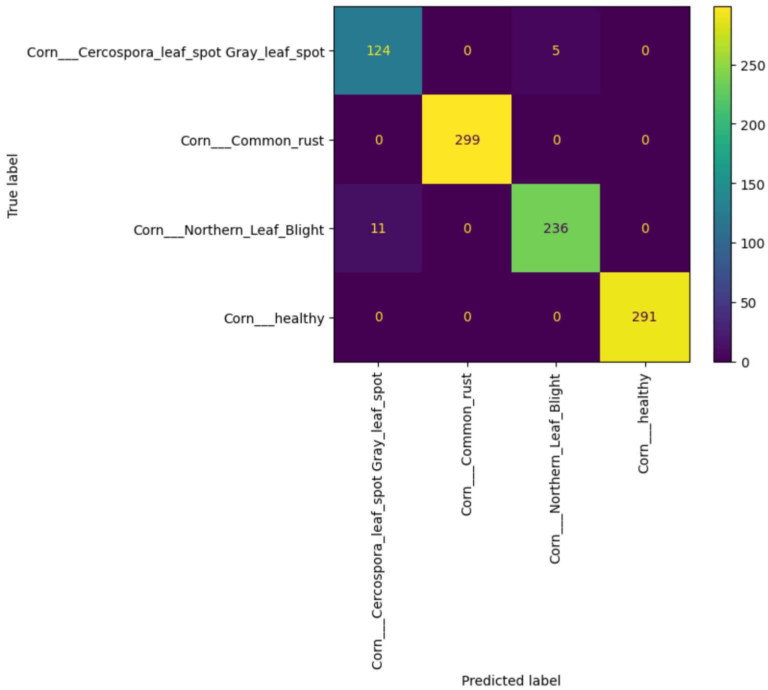

Figure 4.12: Xception model's Confusion Matrix.

Class	Precision	Recall	F1-score
Cercospora leaf spot & gray leaf spot	0.91852	0.96124	0.93939
Common Rust	1.00000	1.00000	1.00000
Northern Leaf Blight	0.97925	0.95547	0.96721
Healthy leaf	1.00000	1.00000	1.00000

4.1.5 EfficientNetV2S

For the final run of experimenting with CNN model, we used the EfficiennetV2S. This model also ran with the same hyperparameters as the previous models, batch size of 32 and learning rate initially set to 0.0001 for 20 epochs and then for 30 epochs 0.00001 using a scheduler function which is called during callback. We similarly used

Keras Checkpoint to save the model with the highest validation accuracy. And this time EfficiennetV2S resulted in an accuracy of 0.9818. After that, We evaluated the model on the testing set and the model achieved an accuracy of 0.98654. Figure 4.15 shows the training and validation losses of the model and Figure 4.14 shows the training and validation accuracies of the model's full training process. Moreover, we also showed the Precision, Recall and F1 scores of the model's testing set in table. Finally, we showed the confusion matrix of the model on testing set in Figure 4.15 for each classes.

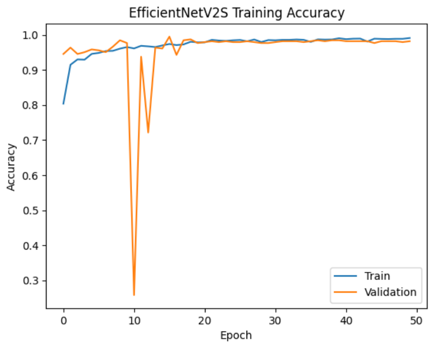

Figure 4.13: EfficientNetV2S model's train and validaiton accuracy.

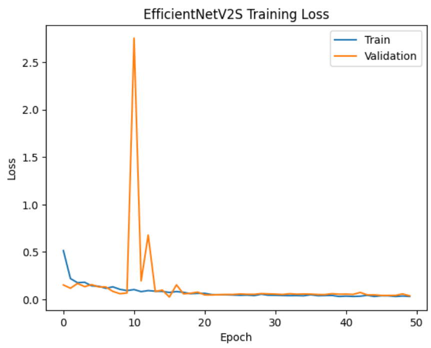

Figure 4.14: EfficientNetV2S model's train and validation loss.

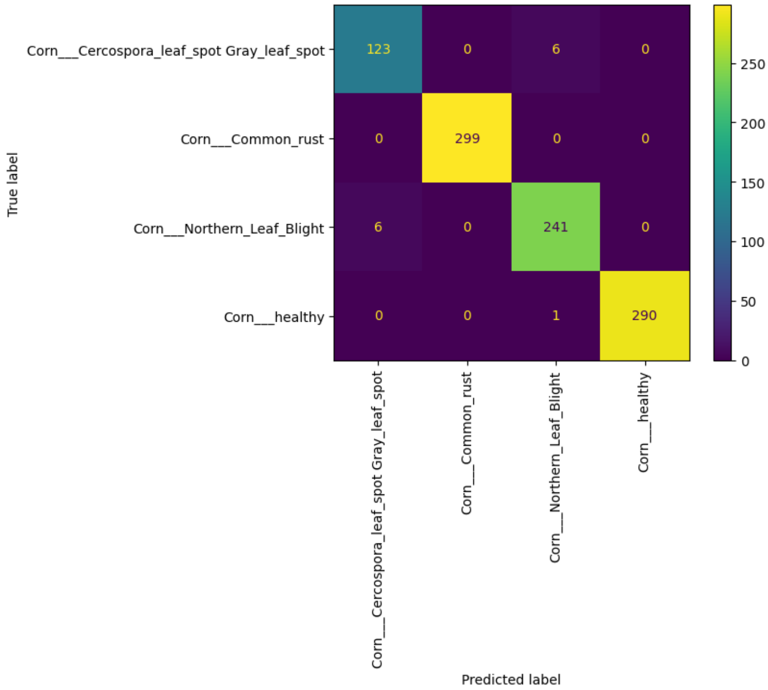

Figure 4.15: EfficientNetV2S model's Confusion Matrix.

Class	Precision	Recall	F1-score
Cercospora leaf spot & gray leaf spot	0.96183	0.97674	0.96923
Common Rust	1.00000	1.00000	1.00000
Northern Leaf Blight	0.98776	0.97976	0.98374
Healthy leaf	1.00000	1.00000	1.00000

4.1.6 Incorporating CNN Features using Machine Learning Classifiers

On this approach, we removed the dense layers after the GlobalAveragePooling2D layer on all of the trained convolutional neural network models. Because of this, when an image is used to predict the probability of each of the 4 classes by the models, instead of returning a probability the models will return a 1-D matrix. This is because now the GlobalPooling layer is the final layer in the models. Based on the K-Nearest Neighbour algorithm, this approach won't need validation data, so we used both train and validation data for training this KNN model. Now, to fit this machine learning model, we first extract the Features from GlobalAveragePooling2D layers of all the CNN models from the train and validation images and then concatenate them. In total, 3096 images from the train and 384 images validation set were used to extract the features. Moreover, the 5 CNN models' GlobalPooling layers returned respectively, DenseNet 1028 elements, Inception and Xception 2048 elements, InceptionResNetV2 1536 elements and EfficientNetV2s elements. Next, we combined all the features which resulted in a 1-D matrix of 7936 elements for a total of 3480 images. So, the resulting 2-D matrix from the images' features had the

shape (3480, 7936). Furthermore, features extracted from the training and validation data were shuffled and 100 samples were taken for implementing GridSearch. During the GridSearch process, we evaluated for the number of nearest neighbors within the range of 1 to 50 and the best parameter for nearest neighbor resulted in 1. After that, we use the features of train and validation images to fit this KNN model and we also set the number of neighbors to 1 (basically indicates fine-KNN's characteristics) which was the best value achieved through GridSearch.
For Support Vector Classifier, we ran the GridSearch using Regularization Parameter set to 0.1,1, 10 and 100, Gamma set to 1, 0.1, 0.01 and 0.001 and Kernel set to RBF, Poly and Sigmoid and the best parameters we got was 1 for Regularization Parameter, 0.001 for Gamma and RBF kernel. Finally, we used these parameters to train SVC using the features extracted from Training and Validation sets.
Similarly, the 5 CNN models were again used to extract the features from the test images using the GlobalAveragePooling2D layers and then concatenate the features. In total 966 images were used to extract features from the test set, resulting in a 2-D matrix of (966, 7936). Finally, these machine learning models were used to predict on the resulting features extracted from the test set. And this time, the accuracy resulted in 0.99586 for KNN and 0.99379 for SVC, thus KNN managed to achieve the highest accuracy which overcame all our previous experiments's accuracies we have done with the CNN architectures.

Classification report of KNN:

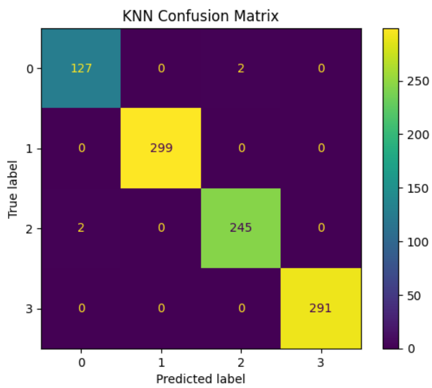

Figure 4.16: Confusion matrix of KNN

Class	Precision	Recall	F1-score
Cercospora leaf spot & gray leaf spot	0.98450	0.98450	0.98450
Common Rust	1.00000	1.00000	1.00000
Northern Leaf Blight	0.99190	0.99190	0.99190
Healthy leaf	1.00000	1.00000	1.00000

Classification report of SVC:

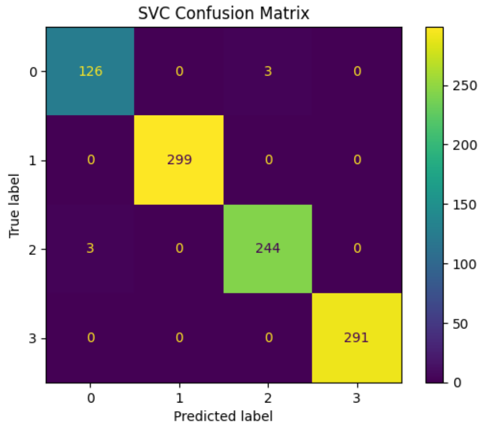

Figure 4.17: Confusion matrix of SVC

Class	Precision	Recall	F1-score
Cercospora leaf spot & gray leaf spot	0.97674	0.97674	0.97674
Common Rust	1.00000	1.00000	1.00000
Northern Leaf Blight	0.98785	0.98785	0.98785
Healthy leaf	1.00000	1.00000	1.00000

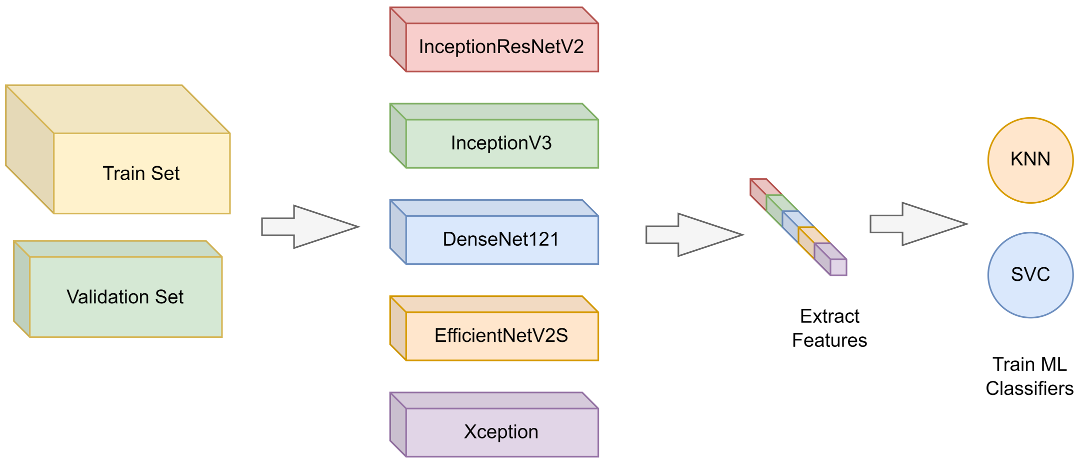

Figure 4.18: ML classifier training process

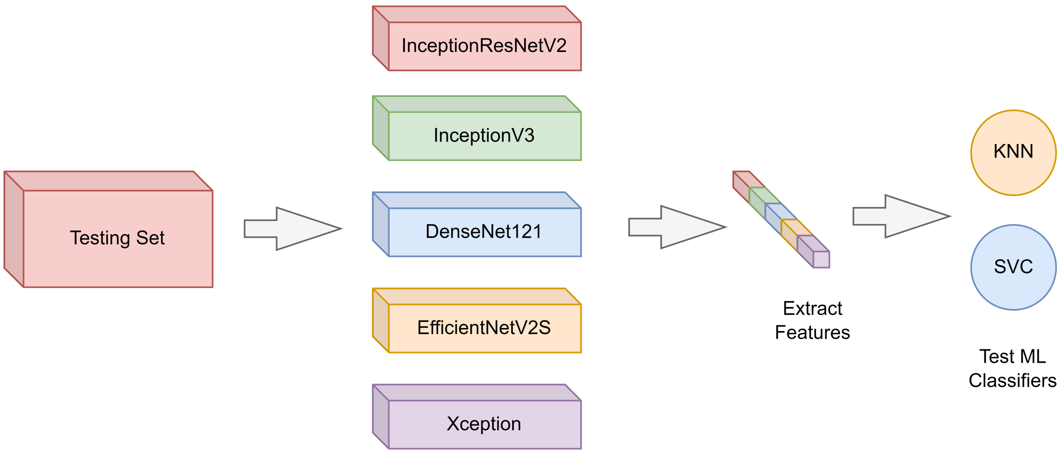

Figure 4.19: ML classifier test process

4.2 Evaluation of Results

The tables provide a comprehensive overview of model characteristics and their performance metrics. The tables highlight K-Nearest Neighbors (KNN) and Support Vector Classifier (SVC) as standout performers with exceptional accuracies and overall evaluation metrics.

The summary of implemented models:

Models	Total Parameters	Trainable Parameters	Non-trainable Parameters
DenseNet121	7,041,604	6,957,956	83,648
InceptionResNetV2	54,342,884	54,282,340	60,544
Inception-v3	21,810,980	21,776,548	34,432
Xception	20,869,676	20,815,148	54,528
EfficientNetV2S	20,336,484	20,182,612	153,872

Results of the implemented CNNs models:

Precisions, recalls and F1-scores mentioned in the table are given as weighted averages.

Models	Accuracy Score	Precision	Recall	F1-score
DenseNet121	0.9896	0.98988	0.98965	0.98969
InceptionResNetV2	0.9917	0.99177	0.99172	0.99173
Inception-v3	0.98964	0.98981	0.98965	0.98968
Xception	0.9834	0.98381	0.98344	0.98352
EfficientNetV2S	0.9865	0.98657	0.98654	0.98656

After this procedures, we extracted features from images of train and validation, where we concatenated 5 CNNs models GlobalAveragePooling2D feature and used them in training ML classifiers. Moreover, we extracted the penultimate layer's activations as features from the testing set and used them in testing the ML classifiers. Basically, we splitted the data of ML classifiers training and testing sets in a ratio of 75% and 25%.

Results of the ML classifiers (after extracting features from CNNs models):

Precisions, recalls and F1-scores mentioned in the table are given as weighted averages.

Models	Accuracy Score	Precision	Recall	F1-score
KNN	0.9958	0.9958	0.9958	0.9958
SVC	0.9938	0.9937	0.9937	0.9937

4.3 Discussion

Among all the models and classifiers, KNNs 0.99586 accuracy score is the highest. This shows that, for this particular classification challenge, KNN has the lowest error rate. Although SVC doesn't match up with KNN's accuracy score but still it performed outstandingly, with an accuracy of 0.99379. Both the classifiers showcased very accurate when applied to this problem.
Moreover, the implemented deep learning CNNs models like InceptionNetV2's accuracy of 0.99172 places next, after KNN and SVC. DenseNet and InceptionV3 are both somewhat less accurate than the best-performing models with an accuracy score of 0.98965. In terms of precision, they are tied. The 0.98654 accuracy achieved by EfficientNetV2S is still very respectable, however it falls just short of the best models. With an accuracy score of 0.98344, Xception lags a little behind among the models we considered. Even though it's accuracy of 0.98344 is the lowest in this comparison, it's still extremely good and Xception may do very well in other settings.
In conclusion, the classifiers with the highest accuracy are the K-Nearest Neighbours (KNN) and Support Vector Classifier (SVC), followed by CNNs model InceptionNetV2. While other CNNs models like EfficientNetV2S and Xception have somewhat lower accuracy scores than DenseNet and InceptionV3, they nevertheless demonstrate respectable performance.

4.3.1 A Review on related researchs on detecting Corn Diseases

Study	Objective	Approach	Performance
Fraiwan et al.[[30]]	Classification (3 diseases + 1 healthy)	Ten CNN models	Accuracy = 98.6%
da Rocha et al.[[22]]	Classification (3 diseases + 1 healthy)	CNN with Bayesian optimization	Accuracy = 97%
Chen et al.[[26]]	Classification (Healthy or diseased)	Mobile-DANet	Identity accuracy = 97.7%
Xu et al.[[28]]	Classification (diseased)	TCI-ALEXN	Accuracy = 93.28%
This Work	Classification (3 diseases + 1 healthy)	CNN models & KNN	Accuracy = **99.59**%
This work	Classification (3 diseases + 1 healthy)	CNN models & SVC	Accuracy = **99.38**%

Chapter 5

Conclusion

Machine learning classifiers that use deep features collected from Convolutional Neural Networks (CNNs) have shown promising results in improving the identification of maize leaf diseases. Using convolutional neural networks (CNNs), this study successfully captured complex disease-related patterns and textures in maize leaf photos. After using these deep characteristics as inputs to several machine learning classifiers, accurate disease identification models could be developed. The work showed promise, with machine learning classifiers demonstrating enhanced accuracy and effectiveness in differentiating between distinct maize leaf diseases after considerable experimentation and hyperparameter tuning. Model improvement and new understanding of these classifiers' decision-making processes were also enabled by researchers' forays into ensemble approaches and interpretability methodologies. Accurate and early disease identification is crucial for crop management and yield preservation, therefore the findings of this study have implications for the fields of agriculture and food security. Additional data sources, more sophisticated deep learning architectures, and real-time application in agricultural contexts are all areas that could be explored in future work to improve the practical usability and impact of this disease identification approach. Overall, the results of this work highlight the promise of integrating deep learning and machine learning to tackle pressing issues in agricultural disease control and so enhance crop vitality and worldwide food safety.

5.1 Challenges

While it's encouraging that deep learning models have been successfully implemented for maize disease diagnosis, the process is not without it's share of obstacles. Several obstacles arise on the road to creating a strong and practical answer as we dive deeper into the world of utilizing AI for agriculture. These difficulties span from the quantity and quality of available data to the viability of implementing cutting-edge models in operational agricultural contexts. Although there are differences amongst the challenges, they all highlight the importance of taking a comprehensive strategy. Some of the challenges are,

- **Data Quality and Quantity:** Training CNNs requires high-quality and diverse datasets, which can be difficult to get. It is essential that the statistics adequately portray the varying stages of the disease, its severity, and the surrounding environment.

- **Generalization:** It is still difficult to ensure the model is applicable in a wide variety of settings. Disease expression may be modified by differences in soil, climate, and farming techniques.

- **Interpretability:** Due to the difficulty in understanding its reasoning, many people refer to CNNs and other deep learning models as black boxes. More work is needed to ensure that these models can be understood by their intended audiences.
- **Hardware and Infrastructure:** The availability of sufficient computer power and infrastructure, however, may be lacking in rural agricultural areas, making it difficult to deploy advanced deep-learning models in the field.
- **Costing criteria:** It can be costly to develop, train and deploy such systems. Finding an acceptable medium between effectiveness and efficiency is crucial.

Resolving these issues is crucial for fully realizing deep learning's potential in agricultural disease detection. We can make our way through the maze of data, model generalizability, interpretability, infrastructure and cost-effectiveness with the help of diligent study, creative thinking and teamwork. To achieve our goal of making agriculture smarter and more resilient, we must first overcome these obstacles. Doing so will improve food security and pave the path for a more sustainable, technologically advanced agricultural future. Taking on these obstacles is essential if we want to see deep learning's benefits implemented in areas where they are most needed.

5.2 Future Scopes

The future holds many promising prospects for research and development in the attempts to improve maize disease detection. Future possibilities in agriculture are hinted at by the groundwork laid by the application of deep learning methods. These prospective horizons foresee a wider application of this technology over a wide range of plant species and agricultural landscapes and promise to improve the accuracy and efficiency of disease identification. Some future scopes that might appear in the near future can be,

- **Multi-Disease Detection:** The ability to detect numerous illnesses in the same plant or field would be a major improvement. When CNN characteristics are combined with sophisticated machine learning approaches, such ensemble methods, the system's capacity to manage multiple diseases at once is greatly improved.
- **Enhanced Disease Identification:** The accuracy of illness identification can be further enhanced by incorporating deep features from CNNs into machine learning classifiers. In the future, scientists can work to perfect CNN architectures tailored to plant disease recognition.
- **Real-Time Monitoring:** By extending this technique to continuous crop monitoring, farmers will be able to respond rapidly to any signs of disease. This may necessitate the creation of mobile or drone-based technologies for rapid illness diagnosis.
- **Desease Detection in Different Species of Plants:** Future research in this field could benefit from extending disease detection technologies to include a wider range of plant species. Although this discussion has primarily centred on maize, the application of the deep learning models and techniques that have been created to other crop species can greatly improve agricultural sustainability and food security. The framework it generates has the potential to revolutionize plant disease control across a wide variety of crops, ultimately tackling larger agricultural concerns on a worldwide scale.

These projected perspectives hold the possibility of not only revolutionizing the way we defend our crops, but of expanding our horizons to encompass a more sustainable and resilient agricultural environment, as we go into the future of maize disease detection and agricultural technology. We can assure worldwide food security and agricultural prosperity by embracing these trends of the future and introducing a new era in which artificial intelligence and plant science collaborate in harmony.

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