Deep Learning for Plant Disease Detection

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ABSTRACT: Agriculture, an essential bedrock of human survival, continually grapples with the menace of plant diseases, culminating in substantial yield reductions. While conventional detection techniques remain widespread, they often entail laborious efforts and are susceptible to inaccuracies, underscoring the pressing need for more efficient, scalable, and immediate solutions. Our research explores the transformative capabilities of Deep Learning (DL) models, primarily focusing on Convolutional Neural Networks (CNNs) and MobileNet architectures in the early and precise identification of plant ailments. We augmented our exploration by incorporating eXplainable Artificial Intelligence (XAI) through GradCAM, which elucidated the decision-making process of these models, providing a visual interpretation of disease indicators in plant images. Through rigorous testing, our CNN model yielded an accuracy of 89%, a precision and recall of 96%, and an F1-score of 96%. Conversely, the MobileNet design showcased an accuracy of 96% but recorded slightly lesser precision, recall, and F1-scores of 90%, 89%, and 89%, respectively. Such results amplify the transformative role of DL in redefining plant disease detection methodologies, presenting a formidable counterpart to conventional techniques and ushering in an era of heightened agricultural security.

Keywords: Agriculture, Plant diseases, Automated disease detection, Deep Learning (DL), Convolutional Neural Networks (CNN), MobileNet.

1. INTRODUCTION

Agriculture, a cornerstone of human civilization, is critical in sustaining life across the globe, providing nourishment to billions [1]. Its origins are as ancient as society, weaving a complex tapestry that binds human survival to the land. The immense significance of agriculture is highlighted in regions like India, where farming is not only an economic activity but a way of life for the vast majority of the population [2]. From small subsistence farms to large commercial agricultural establishments, the cultivation of crops is central to human existence. Yet, this vital industry faces challenges as ancient as the practice: diseases caused by bacteria, fungi, viruses, and other microorganisms [3, 4]. These invisible enemies constantly threaten the very essence of agriculture, undermining food security and sustainability. Globally, plants are fundamental to food provision. However, they are susceptible to diseases due to various environmental factors, leading to notable production deficits. Though prevalent, Traditional manual detection methods are labor-intensive and prone to errors, making them less reliable for early disease identification and containment [5]. Addressing these diseases promptly can significantly bolster yields, potentially enhancing productivity by over 60% [6]. In this context, Convolutional Neural Networks (CNNs) have emerged as a formidable tool, especially adept at deciphering intricate patterns in large datasets, such as images, offering a promising alternative for disease detection [7]. These diseases can wreak havoc on crops, leading to catastrophic effects on both local and global scales. The Irish famine of 1840 illustrates the historical consequences of plant disease, where the blight of potatoes led to the loss of life and mass immigration, changing the demographic landscape [8]. Such tragedies are stark reminders of the potential devastation that unchecked plant diseases can unleash. Even today, the threat persists with staggering financial implications, such as more than 220 billion in losses worldwide [9]. Diseases like cassava mosaic and cassava brown streak in sub-Saharan Africa have effects that ripple across economies, affecting livelihoods, trade, and entire agricultural ecosystems [10]. Traditional methods of detection and control, whether relying on human expertise or chemical interventions, face significant challenges [11, 12]. The process of identifying specific symptoms in various plant parts requires specialized knowledge, labor, and time. Often, this can be slow and ineffective, especially in remote or resource-poor regions. The extensive use of chemical control methods has further led to environmental pollution and the development of pathogen resistance [13, 14]. This complexity is only magnified by the varied species and manifestations of diseases [15], making a one-size-fits-all approach inadequate and impractical. The urgency for early detection cannot be overstated, especially considering the necessity for timely intervention to mitigate the significant threats to food availability, quality, and accessibility [16, 17]. As the global population continues to grow, so does the demand for food. Traditional methods often fall short in scalability and efficiency, and the development of

novel, technology-driven approaches has become paramount. New paradigms are needed to bridge the gap between detection and action to ensure that the world's food supply remains resilient and robust. Deep Learning (DL), a branch of artificial intelligence, has emerged as a promising solution [18,19]. Leveraging advanced techniques like convolutional neural networks (CNNs), DL models can analyze high-resolution images to detect even the most subtle signs of disease [20–23]. This technology has the potential to revolutionize disease detection, transforming a process that once required extensive human intervention into one that can be automated and scaled. Whether providing immediate support to regions lacking in agronomic infrastructure or integrating autonomous vehicles in large-scale agriculture, the possibilities are vast and groundbreaking [24, 25]. However, challenges remain. Existing models often specialize in particular diseases or species, hindering their broad application [26]. The call for robust, adaptable models has led to innovations like transfer learning, which aims to make disease detection tools more efficient and universally applicable [27]. As the field continues to evolve, ongoing research and collaboration among scientists, agronomists, and technologists are essential. The convergence of traditional agricultural wisdom with cutting-edge technology opens the door to an exciting future where the promise of sustainable, resilient, and abundant agriculture may finally be realized. Artificial intelligence, with a specific emphasis on Deep Learning (DL), has ushered in revolutionary advances in plant disease detection in recent times [28, 29]. Due to their ability to manage large and intricate images, DL models are aptly suited for analyzing high-resolution visuals [30]. The advent of Graphical Processing Units (GPUs) and innovative embedded processors has catalyzed the proliferation of DL applications, paving the way for the practical implementation of sophisticated techniques like convolutional neural networks (CNNs) [31]. Notably, these CNN models exhibit prowess in identifying nuanced symptoms, which conventional image processing techniques often overlook [32–34]. The subsequent sections of this study are organized as follows: Section 2 offers a deep dive into contemporary research related to our study. Section 3 outlines the foundational knowledge of the classifiers utilized. Our proposed methodology is detailed in Section 4. Section 5 is earmarked for a discourse on our research findings. We conclude in Section 6, where we encapsulate the essence of our research and propose potential directions for subsequent investigations.

Chen et al.'s 2020 [35] paper delves into the profound effects of plant diseases (PDs) on the food chain. The authors advocate for the use of deep learning (DL) in the automated detection and diagnosis of PDs, emphasizing the transfer learning (TL) capabilities of pre-trained Convolutional Neural Networks (CNNs). The method displayed notable results by leveraging VGGNet, initially trained on ImageNet, in conjunction with the Inception module. It attained a validation accuracy of 91.83% on a public dataset and an average accuracy of 92.00% when predicting rice plant image classifications, even in scenarios with intricate backgrounds. Sunil et al.'s 2022 [36] publication delves into the challenges of catering to an expanding population and the repercussions of plant diseases (PDs) on crop yields. They put forth an economical approach for early PD detection by analyzing plant leaf images using a combination of deep learning models, notably AlexNet, ResNet50, and VGG16. When tested across various plant leaf image datasets, this method demonstrated outstanding accuracy, achieving 100% for binary datasets and a close 99.53% for multi-class datasets. These findings validate the effectiveness of their proposed method in accurately identifying PDs. In their 2020 study, Gayathri et al. [37] presented a deep learning method tailored for the real-time detection of the primary five apple leaf diseases using enhanced Convolutional Neural Networks (CNNs). This method utilized the GoogLeNet Inception framework and incorporated Rainbow concatenation. Additionally, they developed a novel apple leaf disease dataset (ALDD) by leveraging data augmentation and image annotation methodologies. Their innovative INAR-SSD model, trained on a comprehensive set of 26,377 images of diseased apple leaves, secured a notable detection accuracy of 78.80% mAP on the ALDD dataset and boasted a swift detection rate of 23.13 FPS. These outcomes underscore the efficacy of the INAR-SSD model in promptly and accurately diagnosing apple leaf diseases, surpassing the performance benchmarks set by prior methods. Jiang et al. (2019) [38] introduced a deep learning approach for real-time detection of the five primary types of apple leaf diseases using advanced convolutional neural networks (CNNs). They employed the GoogLeNet Inception architecture combined with Rainbow concatenation. Furthermore, they curated a new dataset for apple leaf diseases (ALDD) through data augmentation and image annotation techniques. Their INAR-SSD model, trained on 26,377 images of diseased apple leaves, achieved a detection accuracy of 78.80% mAP on the ALDD dataset, with an impressive detection speed of 23.13 FPS. This suggests that the INAR-SSD model stands out as an efficient tool for early apple leaf disease detection, offering improved accuracy and speed compared to previous methods. In their work, [39] unveiled a groundbreaking method for identifying plant diseases through leaf image categorization using deep convolutional networks. Utilizing the Caffe Deep Learning framework, their model demonstrated remarkable accuracy, with precision levels varying between 91% and 98% for the identification of 13 distinct plant diseases. The paper elaborates extensively on the employed methodology, shedding light on the intricate training steps essential for effectively deploying the disease recognition system. In their research, [40] undertook a comparative analysis of transfer learning situations using CNN architectures such as VGG-16 and VGG-19. They juxtaposed these with their

proposed CNN structures tailored for olive plant disease identification. The study utilized a dataset of 3,400 olive leaf images, and by integrating a data augmentation technique, they expanded this dataset. Notably, the model's accuracy (ACC) experienced an uplift, surging from around 88% to close to 95% post-data augmentation. This research put forth an innovative method for plant disease identification, utilizing leaf image classification in conjunction with deep convolutional networks [41]. The model was developed and trained using the Caffe Deep Learning (DL) architecture. Demonstrating remarkable efficacy, it attained high precision levels ranging between 91% and 98% in accurately recognizing 13 distinct plant disease types.

2. Background

2.1. Convolution Neural Network

Artificial Neural Networks (ANNs) are computational models inspired by the human brain's capacity for analysis and information processing [42]. Like the human brain, an ANN is characterized by a network of interconnected nodes or "neurons" forming a directed graph. These networks excel at recognizing intricate patterns and models that might be too nuanced for either humans or traditional computational techniques. When trained effectively, an ANN functions as a domain-specific expert, capable of predicting outcomes for new data and addressing hypothetical scenarios, making it a tool apt for "what-if" analyses [43]. There are diverse categories of neural networks, such as Recurrent Neural Networks (RNN), Multilayer Perceptrons (MLP), and Convolutional Neural Networks (CNN), to name a few. While MLPs, regular neural networks, were initially employed for image classification, they soon proved to be computationally demanding and parameter-heavy with the increasing resolution of images. CNNs were introduced to counteract these limitations. Unlike traditional networks, CNNs possess neurons structured in three dimensions - width, height, and depth, making them tailored for image data [44]. Their inherent design, optimized for understanding the 3D spatial hierarchy of images, has solidified CNNs as the go-to choice for image-related tasks. A standard CNN structure predominantly comprises three key layers: the Convolutional layer, the Pooling layer, and the Fully Connected layer.

2.2. Transfert Learning

Transfer learning (TL) is an ML strategy where knowledge from one task is leveraged to improve performance on a related, subsequent task. This technique adapts a model pre-trained on a particular problem to tackle a different but associated challenge. As highlighted by Torrey and Shavlik (2010) [45], this pre-trained model can be rooted in deep learning or any other machine learning framework. The core principle of TL is the portability of knowledge. Insights and feature patterns extracted from one context can provide a head start when approaching a new problem, often reducing the computational cost and time to train. This efficiency makes TL especially popular in fields like computer vision (CV) and natural language processing (NLP), where large, adaptable pre-trained models are prevalent. Beyond these, TL also finds utility in diverse applications such as recommendation engines and auditory signal processing.

2.3. MobileNet

MobileNet, a CNN architecture, emerged from Google in 2017, targeting efficient image processing on mobile and embedded platforms [46]. By leveraging depthwise separable convolutions, the computational expense gets significantly reduced. MobileNet has two primary versions: MobileNet V1, with 28 convolutional layers, and V2, boasting 53 layers. Both have been pre-trained on expansive datasets like ImageNet. In transfer learning (TL), these models can be tailored to new tasks by updating the final classification layer and training on specific datasets for new objectives. MobileNet excels in numerous computer vision (CV) tasks, including object detection, image segmentation, and facial recognition, demonstrating computational efficiency and fewer parameter requirements than many deep neural networks (DNN) structures.

3. METHOD

In the methodology framework for our investigation, the initial step centers around dataset acquisition. Here, pertinent data is meticulously gathered, laying the groundwork for our analytical pursuits. Subsequent to this, data preprocessing techniques come into play, enhancing data quality and preparing it for intricate analyses. As the prepared data stands poised for exploration, we segue into the modeling phase. At this juncture, we deploy two distinct neural network designs: the well-established Convolutional Neural Network (CNN) and the streamlined MobileNet architecture. Integrating eXplainable Artificial Intelligence (XAI) into our

approach, we also incorporate GradCAM, offering a layer of interpretability. This facilitates a visual representation of how these models discern patterns and make decisions, further enriching our understanding. The juxtaposition of these two architectures ensures a multifaceted perspective, shedding light on their individual strengths, nuances, and performance metrics, especially in relation to our dataset. The outcomes from these models undergo rigorous scrutiny, wherein their results are dissected, insights extracted, and their overall efficacy in addressing the research objectives is meticulously assessed.
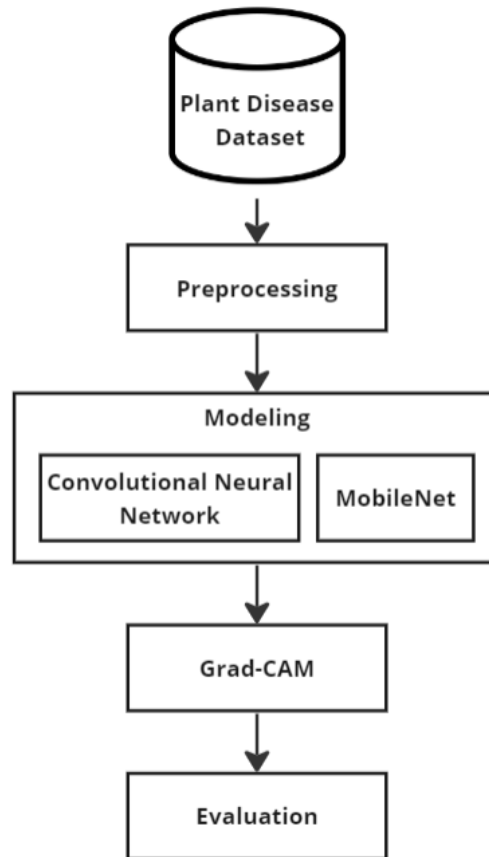

Figure 1. The methodology pipeline.

3.1. Dataset

This study employs a rich dataset consisting of nearly 87,000 RGB leaf images of crops. These images span 38 distinct classes, encompassing both healthy and afflicted specimens. For effective model development and assessment, the data is apportioned into training and validation subsets, with an 80/20 split, preserving the inherent directory hierarchy. An exclusive directory with 33 images is also constituted solely for prediction tasks. Notably, this dataset can be accessed on Kaggle, presenting an open resource for enthusiasts delving into plant disease identification and categorization.

3.2. Pre-processing

In this study, the preprocessing stages are instrumental in setting the data up for phases like model training and assessment. The data selection phase involves choosing a specific subset of labels, emphasizing 20 unique classes from each directory for deeper scrutiny. Such a choice streamlines the study's focus while ensuring a balanced representation. Following this, images are resized to a consistent dimension of 224 x 224 pixels, a step that's indispensable for ensuring they fit the input constraints of many DL models. Finally, each

image undergoes normalization, dividing pixel values by 255. By doing so, pixel values are scaled between 0 and 1, a measure that standardizes the dataset, priming it for efficient deep-learning model processing.

3.3. Modeling

3.3.1. CNN classifier

For the initial classification approach in this investigation, a CNN is constructed utilizing the TensorFlow platform. This CNN design commences with a 2D convolutional layer, which is subsequently complemented by a max pooling layer to condense spatial dimensions. This sequence is reiterated, integrating a dropout layer to counteract overfitting. Once flattened, the data transitions through dense layers. The terminal layer adopts the softmax activation mechanism to facilitate multi-class categorization. The inherent adaptability of the CNN design permits tailored modifications suited to the distinct classification objective and the dataset at hand.

3.3.2. MobileNet classifier

This research employs the MobileNetV2 framework, which builds upon the foundational MobileNet architecture [15]. What distinguishes MobileNetV2 is its introduction of linear bottlenecks interspersed between layers and the inclusion of shortcut connections spanning these bottlenecks. Like its predecessors, MobileNetV2 benefits from pretraining on the ImageNet dataset, granting it robust feature extraction capabilities. Adapting it for our specific classification task entails removing the upper layers originally geared towards ImageNet classification. The resultant output from the base MobileNetV2 is then channeled through a sequence of four Dense layers, all utilizing the 'relu' activation function, with each layer having progressively fewer nodes. To counteract potential overfitting, dropout layers are integrated after each Dense layer. The concluding Dense layer, furnished with 20 nodes and a 'softmax' activation function, is optimized for multi-class categorization. To materialize this structure, we employed the Keras API from Tensor-Flow, configuring it to accept input images of dimensions (224, 224, 3) and produce a probability distribution spanning the 20 classes.

3.4. Explaining AI with Grad-CAM Techniques

In this study, we employ the sophisticated Grad-CAM technique, also known as Gradient-Weighted Class Activation Mapping [47]. This method offers in-depth insights by providing explanations corresponding to each input. Specifically, it yields an intuitive visualization that indicates the significance of individual pixels when assessed by trained deep-learning algorithms. Grad-CAM stands out as a notable tool in the realm of Explainable Artificial Intelligence (XAI), gaining widespread recognition and application in various computer vision challenges. Given that our research primarily revolves around image-based data from three distinct experiments, we chose the dependable Grad-CAM approach as our representative XAI technique. While there are various other XAI methodologies available, for the purposes of this study, we solely focus on Grad-CAM without delving into comparisons or discussions regarding the differences in their explanatory outcomes. It's worth noting that the foundational concepts of Grad-CAM draw inspiration from the class activation map (CAM) techniques [48]. An intrinsic characteristic of Grad-CAM is its ability to utilize gradient information accumulated during the training phase. This allows for the identification of the relative importance of neurons within the model's decision-making framework. In essence, neurons that exhibit larger absolute gradient values are deemed more pivotal in influencing the model's conclusions.

4.   RESULTS AND DISCUSSION

4.1. Training parameters

The deep learning models were calibrated using the parameters outlined below (Table 1):

- Classes: The dataset was segmented into 20 distinct categories, guiding the models in clas- sifying diverse data entries.
- Epochs: Each model was trained over a span of 20 epochs, meaning they iteratively learned from the dataset 20 times.
- Loss Function: Sparse Categorical Cross Entropy was designated the loss function, a preferred choice for multi-class classification tasks.

- Optimization Algorithm: ADAM was employed as the optimization strategy, renowned for its effectiveness in managing stochastic objectives utilizing first-order gradient data.
- Batch Size: A batch configuration of 64 was set, processing 64 dataset samples during each iteration of model parameter updates.
- Validation Data: A fifth of the dataset, precisely 20%, was earmarked for validation, enabling real-time performance assessment throughout the training phase.
- Image Dimensions: All input images were resized to dimensions of 224 x 224 pixels to maintain consistency. The models were poised to achieve optimal performance and learning efficiency by adhering to these specific configurations.

Table 1. Training Configuration for DL Models

Parameter	Value/Description
Classes	20 distinct categories
Epochs	20
Loss Function	Sparse Categorical Cross Entropy
Optimization Algorithm	ADAM
Batch Size	64
Validation Split	20% of the dataset
Image Dimensions	224 x 224 pixels

4.2. Results for CNN Classification

The performance metrics, including Precision (PRE), Recall (REC), and F-Score (F-S), were computed for every class involved in the classification. The Grape_Esca_(Black_Measles) class demonstrated exemplary performance with a top precision score of 99%, signifying a stellar accuracy in pinpointing positive cases. Meanwhile, the Orange_Haunglongbing_(Citrus_greening) class achieved an outstanding recall score of 100%, ensuring thorough recognition of all positive instances. The balanced metric, F-Score, was highest for Grape_Esca_(Black_Measles) at 98%, indicating a harmonious blend of precision and recall. In contrast, the Tomato_Early_blight class lagged with the lowest precision at 62%, suggesting potential misclassifications. The Tomato_Late_blight class had the lowest recall score of 75%, which implies some misses in detecting true positive cases. Tomato_Early_blight also fell behind its F-Score by 71%, pointing to a compromised balance between precision and recall.

4.3. MobileNet Results

The evaluation results reveal the classification task's highest and lowest PRE, REC, and F-S values. The class with the highest PRE, REC, and F-S is Grape_Esca_(Black_Measles), achieving perfect scores of 100% for all three metrics. This indicates the accurate identification of positive instances for this class. Conversely, Raspberry_healthy also demonstrates excellent performance with PRE, REC, and F-S values of 100%. On the other hand, Tomato_Early_blight exhibits the lowest PRE, REC, and F-S values of 88%, 74%, and 80%, respectively. These lower scores suggest some false positives and negatives in the classification results for this class. The classification model demonstrates high performance with an ACC of 96%, and the macro and weighted averages of PRE, REC, and F-S are 96%, indicating the model's proficiency in accurately predicting most classes.

4.4. Visual Interpretation of Disease Detection

GradCAM is designed to offer clarity in class discrimination by elucidating the areas of focus or concern for each layer of the network during its processing and decision-making phases. This granular insight is pivotal in understanding not only what the model sees but also the importance it attaches to various segments of the input. Figure 2 vividly illustrates this concept by showcasing the heatmaps generated using the GradCAM method. In these heatmaps, varying shades of color, ranging from red to blue, represent different levels of importance or weights as determined by the model. More specifically, the darker shades, whether red or blue, pinpoint the regions in the image that the network deems as carrying significant information. Such regions are the ones that influence the model's decision most strongly. In the context of our study, which revolves around disease detection in plants, these highlighted areas essentially suggest the potential regions of the plant that manifest symptoms of a disease. Consequently, by juxtaposing the original images with their

respective GradCAM heatmaps, Figure 2 provides a visual guide, enabling researchers, agronomists, and readers to appreciate the regions the models classify as indicative of disease presence. This offers a transparent lens through which one can understand and trust the model's predictions, paving the way for more informed decisions in real-world agricultural applications.
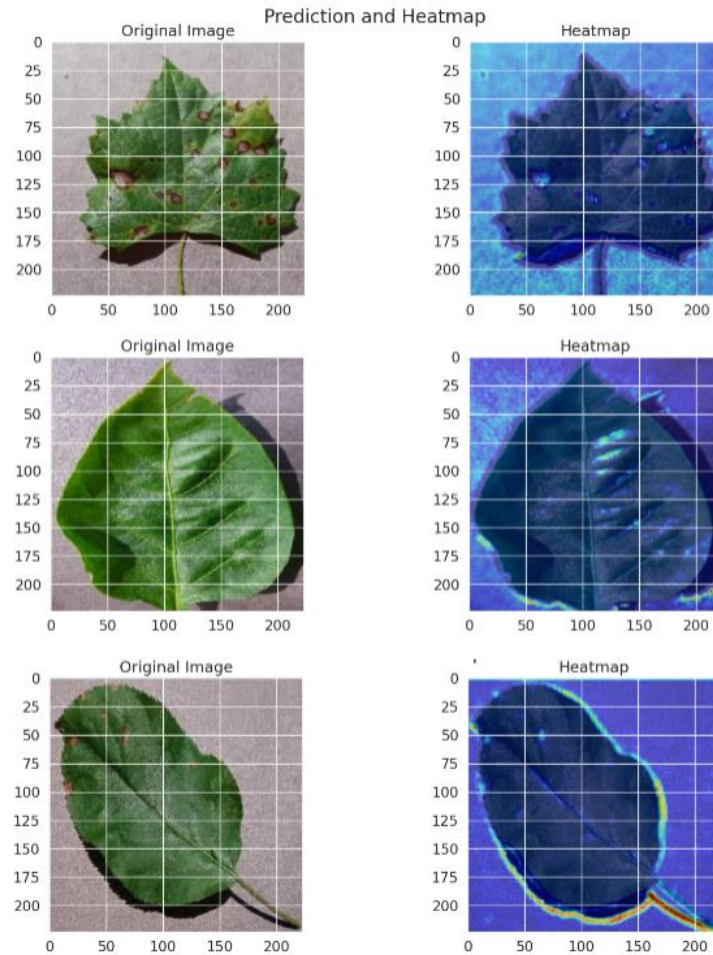

Figure 2. Comparative Analysis of Original Plant Images and Corresponding GradCAM Heatmaps Highlighting Disease Indicators.

4.5. Comparison

Several distinctions emerge in comparing the performance of the CNN and MobileNet classifiers.

The CNN classifier demonstrates strong proficiency in certain classes, like Grape_Esca_(Black_Measles), which achieves the highest Precision (PRE) value of 99% and an F-Score (F-S) of 98%. This performance indicates a balanced blend of precision and recall for this class. However, there are evident challenges with Tomato_Early_blight, which shows a significantly lower PRE of 62% and F-S of 71%. On the other hand, MobileNet boasts impressive results, especially for the Grape_Esca_(Black_Measles) and Raspberry_healthy classes, both achieving perfect scores of 100% across PRE, Recall (REC), and F-S metrics. Nonetheless, even MobileNet stumbles with Tomato_Early_blight, albeit with slightly better scores than CNN, as indicated by its 88% PRE, 74% REC, and 80% F-S. While both models exhibit high levels of accuracy, MobileNet appears to have a more consistent performance, as evidenced by its average accuracy of 96% across classes.

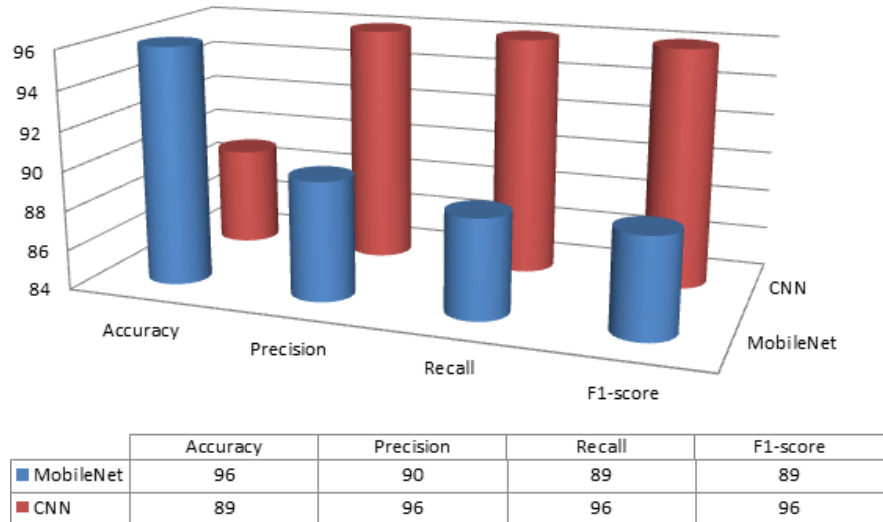|	Accuracy	Precision	Recall	F1-score
■ MobileNet	96	90	89	89
■ CNN	89	96	96	96

Figure 3. CNN and MobileNet results.

5.   CONCLUSION (10 PT)

The imperative of prompt and precise plant disease detection holds heightened relevance in our contemporary era, marked by intensifying calls for food security and ecological sustainability. In our exploration, we harnessed the prowess of DL, specifically the CNN and MobileNet architectures, to tackle this perennial agricultural dilemma. Our findings shed revealing light on the potential of these models. The CNNs exhibited a commendable performance, achieving an accuracy of 89%, complemented by a precision and recall of 96% and an F1-score of 96%. In comparison, the MobileNet architecture, while demonstrating a superior accuracy of 96%, manifested marginally reduced precision, recall, and F1-score values, clocking in at 90%, 89%, and 89%, respectively. Augmenting our investigation was the incorporation of XAI using GradCAM, which added a layer of interpretability to our models, offering visual insights into how these networks discern disease indicators in plant images. Such advancements echo the transformative promise that DL models hold for revolutionizing plant disease detection and proactive management. While our research offers a promising window into this burgeoning domain, the path forward beckons with avenues for further innovation and broadening of scope. Here are some prospective avenues for future research:

- Developing a mobile or web application using the trained models could enable farmers and agricultural experts to detect diseases in real-time, ensuring timely intervention.
- With the proliferation of smart farming tools and sensors, integrating our DL models with Internet of Things (IoT) devices could pave the way for fully automated disease detection systems on farms.

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